A Mixed Methods Examination of the Antecedents of User Self-Disclosure on Digital Health Platforms

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DECLARATION

I hereby certify that this material, which I now submit for assessment on the programme of study leading to the award of PhD is entirely my own work, and that I have exercised reasonable care to ensure that the work is original, and does not to the best of my knowledge breach any law of copyright, and has not been taken from the work of others save and to the extent that such work has been cited and acknowledged within the text of my work.

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Le buíochas ó chroí

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LIST OF ABBREVIATIONS

ASU = Arizona State University

CMB = Common Method Bias

CMC = Computer Mediated Communication

CPM = Communication Privacy Management

DCU = Dublin City University

DHP = Digital Health Platform

EHR = Electronic Health Record

EMR= Electronic Medical Record

FTF = Face to Face

HSE = Health Service Executive

HIPC = Health Information Privacy Concern

IS = Information System

SET = Social Exchange Theory

SIDE = Social Identity Model for Deindividuation Effects

SIP = Social Information Processing

SPT = Social Penetration Theory

THP = Trust in Health Platforms

ABSTRACT

A Mixed Methods Examination of the Antecedents of User Self-Disclosure on Digital Health Platforms.

Eoghan McConalogue

Digital health platforms (DHPs) present the opportunity for individuals to manage their personal health more effectively through seeking and obtaining health advice. However, little is known about the factors that influence self-disclosure on these platforms and are therefore critical for their success.

This research proposes that self-disclosure on a DHP is influenced by trust in health platforms (THP) and health information privacy concerns (HIPC) across different cultures and personalities. Using data from Ireland and the United States, it develops a framework that harnesses social exchange theory (SET) and social penetration theory (SPT) as a lens to understand self-disclosure on DHPs. It examines the factors that generate THP and HIPC. It then determines the influence of THP and HIPC on self-disclosure. Finally, the model offers a unique look at the role of personality traits and the influence they have on likelihood to self-disclose.

A two-stage mixed-methods data collection approach was employed to explore these propositions. Quantitative surveys were used to collect data from 300 participants in Ireland and America. 20 qualitative research interviews were then conducted with Irish and American participants. The quantitative and qualitative findings were then integrated and evaluated in the context of the hypothesised relationships.

The integrated findings show THP is the critical pathway to self-disclosure. THP is shaped by social influence, perceived reciprocity and privacy risk beliefs. HIPC is shown to reduce THP. Personality traits also influence self-disclosure. This study extends SET and SPT to a digital health platform context. The findings provide actionable insights, which can assist policy makers who wish to protect citizen health data and health technology vendors who seek to develop trustworthy platforms.

1 Chapter One: Introduction

1.1 Overview of the Dissertation

This dissertation examines the factors that influence User self-disclosure of personal health information on digital health platforms. It seeks to identify specific factors that can predict or inhibit such self-disclosure within this context. Such insight has become increasingly urgent in a post-pandemic society that is characterised by limited access to medical resources (Kentikelenis and Stubbs, 2022), and accelerating rates of co-morbidity associated with increased longevity (Carannante, D'Amato and Iaccarino, 2022), as well as a corresponding realisation of the need to shift towards preventive rather than reactive care (Waldman and Terzic, 2019; Wang *et al.*, 2021), all of which underpins the need to harness the benefits of Internet technologies to support more effective self-management of health – the success of which is premised on self-disclosure of personal health information. The examination is systematically structured to obtain these insights. To that end, it starts with a review of the literature, which is used to guide the research. This is used to identify core constructs and relationships that merit attention, as well as important theoretical frameworks to guide the study. Gaps in knowledge are identified and hypotheses and their rationale are articulated. Following this, the research model is developed, which is then tested using samples obtained from two different countries. A detailed data analysis employing triangulation of methods is undertaken and the findings are then considered in relation to extant research, with main contributions of the body of knowledge discussed in the context of extant research and how they extend understanding of the factors that influence User self-disclosure of personal health information on digital health platforms.

Illustrating the need for this research, this chapter starts with an overview of digital health platforms which shows that their success is predicated to a large extent on user disclosure. The practical rationale for why it is necessary to understand the predictors of self-disclosure in this context is supported with evidence from practitioners and academic sources which confirms that this research is not just interesting, but important and necessary (Tihanyi, 2020).

1.2 Background of the Research

Digital health platforms (DHPs) are defined as collections of applications and technologies used to support the delivery of healthcare and wellbeing services (ITU, 2017; Alharbi, 2021). These platforms generally adhere to the following disclosure criteria; electronic transmission of health data over distance via cloud servers; the nature of the information can be voice, sound, video, picture, text or geographic; it can include real-time data capture using sensors; be shared with bidirectional communities and peer to peer supports, and the transmission can be asynchronous or synchronous (Brennan *et al.*, 2010; Bittner *et al.*, 2015; Lundell *et al.*, 2015; Frontera *et al.*, 2016; ITU, 2017; Alharbi, 2021). Examples include online health communities that arise from social media platforms such as Facebook or similar (Glynn *et al.*, 2015; Alshakhs and Alanzi, 2018; Afful-dadzie, Afful-dadzie and Egala, 2021), fitness and wellbeing trackers such as FitBit (Quer *et al.*, 2021), personal electronic health records (Crameri, Dam and Prior, 2022), the Seha platform for remote interaction between consumers and their healthcare teams (Alharbi, 2021), the Roche Diabetes Care Platform that allows for self-management of medical administration and data (Roche, 2020), and the Covid Tracker App used to collect and disseminate citizen data about Covid-19 vaccination rates and status (Health Service Executive, 2020).

A fundamental commonality is that these platforms are synonymous with user- and patient-centric, self-management solutions that utilise the application of internet communication technologies and smartphone technologies (Brennan *et al.*, 2010; Bittner *et al.*, 2015; Frontera *et al.*, 2016).

The inherent benefits of DHPs in a healthcare context are evident, ranging from the reduction of economic burdens and stresses on health care systems, to improved patient rehabilitation and citizen wellbeing (Jacquemard *et al.*, 2014; Novitzky *et al.*, 2014; Alfayez *et al.*, 2021; Ghose *et al.*, 2022). For example, in their research Ghose *et al.,* (2022) found that mobile DHPs for chronic illness can have 21.6% stronger impact on positive health outcomes when compared with traditional means of information exchange among diabetes patients, while DHPs assisted in a 17.1% decrease in calories consumed and 14.5% increase in sleep time in the same research. With regard to cost savings Dinesen *et al.*, (2016) reported that self-monitoring DHPs could reduce hospital expenditures by 17% to 75% depending on the severity of illness in question. While the U.S. Veterans Administration saw a 25% reduction in hospital length stays and a 19% reduction in hospital admissions after launching digital health applications for its members (Darkins *et al.*, 2008; Dinesen *et al.*, 2016). In a post Covid-19 world, global citizens have been exposed to DHPs in efforts by governments and health technology vendors to reduce the spread of Covid-19, to disseminate critical public health information and to capture user experiences during and after the pandemic (Rowe, Ngwenyama and Richet, 2020; Alfayez *et al.*, 2021; Alharbi, 2021; Ghose *et al.*, 2022; Schmidt *et al.*, 2022;

Vieira Silva *et al.*, 2022). Examples of this include the Covid-19 tracker app in Ireland which was downloaded over one million times in the first 48 hours after its release and was used to collect and disseminate user data about Covid-19 vaccination rates and status (Health Service Executive, 2020). While researchers in the U.S. developed novel ways to identify possible Covid-19 hotspots by combining user data from fitness trackers and evaluating changes in heart rate, sleep and activity levels, along with self-reported symptom data (Quer *et al.*, 2021).

Moreover, from a patient-empowerment and reach perspective, wearable DHPs that use sensors, such as Fitbits, are estimated to reach over 700 million individuals users by 2024 (Laricchia, 2022). These enable tracking of steps, movement, heart rate, ECG data, menstrual cycle, mood and sleep patterns (Al-Alusi *et al.*, 2019). Similarly, online health communities such as WebMD reach as much as 75 million unique users per month (WebMD, 2018). In fact, such digital platforms mark one of the biggest IT transformations that has occurred since the internet emerged (Lowry, Dinev and Willison, 2017; Istepanian and Al-Anzi, 2018) and more generally can obliterate entire traditional market platforms by virtue of network economies of scale and scope, as witnessed with the rise of the global digital marketplace, Amazon. However, the increased and effective usage of DHPs contains unique characteristics, namely that the successful transmission of advice which can potentially improve the user's management of their health is dependent on user disclosure of personal health data in the first instance - and that disclosure cannot be assumed. For example, FitBit has a 30% abandonment rate (Gartner, 2016), and some research (Nonnecke and Preece, 2001) has shown that lurkers can make up 45.5% of all users in a health support community, with other research (Mierlo, 2014) finding this number may be as high as 90% in the context of a digital health social network designed to facilitate behavioural change. This has practical ramifications as this resistance to actively engage with these DHPs via disclosure limits their potential to provide accurate health guidance and is also concerning from a digital health platform sustainability perspective. It is understandable therefore that researchers such as Yuchao *et al.*, (2021) have emphasised the need to understand the factors which influence or inhibit disclosure of personal health information via online platforms.

While some studies have sought to understand self-disclosure in an online context (Nguyen, Bin and Campbell, 2012), it remains a nascent research domain, particularly with respect to users and their personal health data (Yuchao, Ying and Liao, 2021). As such, the unique nature of DHPs, including the information sensitivity and heightened consequences associated with user self-disclosure in an online context, have caught the attention of the IS research community to the effect that there is a call from researchers such as Anderson and Agarwal, (2011), Nguyen, Bin and Campbell, (2012) and Hallam and Zanella, (2017) to better understand the nature of online self-disclosure, and in particular to focus on its relationship to trust and information privacy concerns (Nguyen, Bin and Campbell, 2012; Wang and Midha, 2012; Hallam and Zanella, 2017; Lowry, Dinev and Willison, 2017; Davazdahemami *et al.*, 2020; Yuchao, Ying and Liao, 2021).

In this study it is argued that there are three main reasons to research this phenomenon. First, the availability of user- and patient-centric DHPs is increasing (Dinesen *et al.*, 2016; Alharbi, 2021; Vieira Silva *et al.*, 2022). If the nature and antecedents of online self-disclosure of personal health information is not understood the inherent health and wellbeing benefits associated with DHPs could for example be dramatically reduced due to a lack of understanding about the inhibiting effects of privacy concerns (Anderson and Agarwal, 2011; Fox and Connolly, 2018). Second, while DHP initiatives have the potential to empower users through increased diffusion of targeted health information and health interventions, the success of these platforms is dependent on user trust and disclosure on these platforms (Sillence *et al.*, 2011; Zhang and Liu, 2022). Without user disclosures, these platforms are rendered useless, but by answering calls to elucidate what constitutes trust in a digital health context (Vega, Montague and DeHart, 2010; Vega, Montague and Dehart, 2011), this study can provide such insights which can be used to foster a positive, trustworthy disclosure environment. As the current global economic climate witnesses budget cutbacks and reduced access to medical resources (Kentikelenis and Stubbs, 2022), such understanding regarding how to more effectively generate trust in DHPs takes on even greater importance for users and healthcare providers. Third, by the year 2025, the global value of DHPs is estimated to be €232 billion (Alharbi, 2021), with 3.7 billion mobile health application downloads occurring by 2017 alone (Stewart, 2019). While these platforms have the potential to improve user wellbeing and reduce the economic burden on health systems, especially during a global pandemic such as Covid-19 (Frontera *et al.*, 2016; Alfayez *et al.*, 2021; Ghose *et al.*, 2022), it is imperative that the phenomenon of self-disclosure on DHPs and the factors that predict or inhibit it are fully understood so as to avoid economic waste.

Consequently, this study extends current knowledge relating to antecedents of self-disclosure in a digital health context, providing a timely insight into the factors and relationships that must be considered in order to create an environment that more effectively supports such disclosure.

1.3 Research Questions

As previously noted, there is much conceptual and operational discussion as to the nature of self-disclosure of personal health information in the context of digital health platforms. Despite the considerable academic diversity, there are certain variables that are widely acknowledged as meriting attention when investigating self-disclosure in an online context. These include trust, privacy, reciprocity, social influence and personality traits (Posey *et al.*, 2010; Nguyen, Bin and Campbell, 2012; Dinesen *et al.*, 2016).

As the primary objective of this research is to investigate what factors influence self-disclosure on DHPs and do these factors vary dependent on national context, the principal research question is '*What factors influence self-disclosure of personal health information by end users of DHPs and what are their inter-relationships?*'

It sets out to answer the primary research question by examining specific antecedents proposed in the extant literature as these have potential to guide a comprehensive investigation. The principal question is therefore subdivided into the following subsidiary questions:

a. *What is the relationship between trust and self-disclosure in this context?*

b. *What is the relationship between HIPC and self-disclosure in this context?*

c. *What is the relationship between HIPC and trust in this context?*

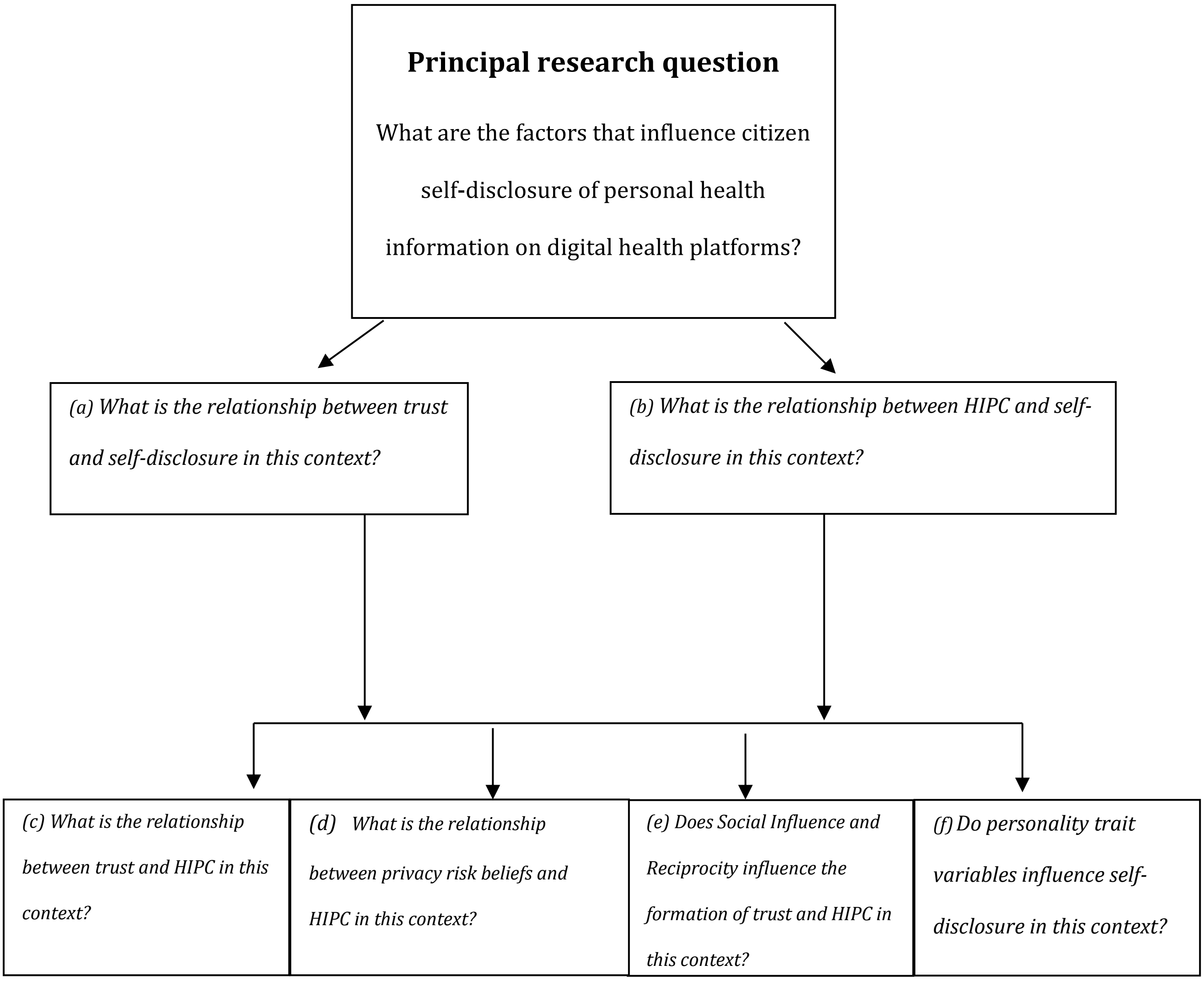
d. *What is the relationship between privacy risk beliefs and HIPC in this context?*

d. *Does (i) Social Influence and (ii) Reciprocity influence the formation of trust or HIPC in this context?*

f. *Do personality trait variables influence self-disclosure in this context?*

In order to determine if these relationships are national culture independent, it examines them via a cross cultural comparison employing samples obtained in the USA and in Ireland.

Figure 1.1 Research Questions



Principal research question

What are the factors that influence citizen self-disclosure of personal health information on digital health platforms?

(a) What is the relationship between trust and self-disclosure in this context?

(b) What is the relationship between HIPC and self-disclosure in this context?

(c) What is the relationship between trust and HIPC in this context?

(d) What is the relationship between privacy risk beliefs and HIPC in this context?

(e) Does Social Influence and Reciprocity influence the formation of trust and HIPC in this context?

(f) Do personality trait variables influence self-disclosure in this context?

1.4 Research Justification

This study can be justified on three grounds. These are:

- There are gaps in the literature.
- The subject is topical both for academics and practitioners.
- There are benefits for future research.

Gaps in the literature: The review of the literature presented in Chapter Two outlines a number of gaps in existing research, in particular a dearth of research on the nature of self-disclosure of health information in an online health context. Seven key gaps are identified:

1) The underlying antecedents of self-disclosure – and their inter-relationships - in an online health context remain underexplored (Nguyen, Bin and Campbell, 2012; Wang and Midha, 2012; Hallam and Zanella, 2017; Lowry, Dinev and Willison, 2017; Davazdahemami *et al.*, 2020; Yuchao, Ying and Liao, 2021). Moreover, while individuals' *intentions* in an online health context have received much attention (Anderson and Agarwal, 2011; Fox and Connolly, 2018), there remains a dearth of research that examines actual online *behavioral responses* pertaining to health (Anderson and Agarwal, 2011; Dinesen *et al.*, 2016). This present research therefore offers to bridge this gap through its examination of online health disclosure as a behavioral response (Faries, 2016).
2) How trust in an online health context is generated and how it influences self-disclosure is matter of speculation that requires more detailed attention (Vega,

Montague and DeHart, 2010; Vega, Montague and Dehart, 2011; Fox and Connolly, 2018). Research on trust to date in the context of self-disclosure in an online health context is not only limited, but what does exist has operationalized the construct in terms of general trust beliefs, assumed a linear direct relationship with self-disclosure that has ignored factors and inter-relationships which might influence generation of trust in this context (e.g., Posey *et al.*, 2010).

3) The literature highlights the necessity of understanding privacy in a digital health context, in particular how privacy concerns are generated in this context and how these concerns influence trust and disclosure behaviours (as opposed to disclosure intentions) (Angst and Agarwal, 2009; Anderson and Agarwal, 2011; Lowry, Dinev and Willison, 2017). However, much research has focused on general privacy concerns, not considered how these relate to more specific health information privacy concerns and how this shapes self-disclosure of personal health information in an online context.
4) There is a lack of understanding as to what role reciprocity and social influence play in the generation of trust and privacy concerns in an online health context (Alaqra and Wästlund, 2019; Khalil, Zia and Abdallah, 2019). Moreover, research which has examined self-disclosure in an online employment context has conceptualised both reciprocity and social influence as having direct linear relationships with self-disclosure, ignoring potential relationships and their more nuanced effect on behavioural outcome. This has limited our understanding of the effect of these constructs and is not consistent with theoretical frameworks (such as Theory of Planned Behaviour (Venkatesh *et al.*, 2003)) which have repeatedly shown that the influence of normative

factors on outcome is not directly expressed. This research helps to clarify the role of both of these constructs and how they are expresssed via the research framework employed in this study.

5) Information systems research focuses on examination of the IT artifact and the individual's response to same in diverse contexts. However, individuals are not a homogenous group and as a consequence, more recently the examination of personality traits in IS literature has gained considerable attention (Barnett *et al.*, 2015; XI Chen, Pan and Guo, 2016; Kim, 2018). However, whether personality traits influence self-disclosure within the context of DHPs remains a matter of speculation to date (Bansal, Zahedi and Gefen, 2010; Nguyen, Bin and Campbell, 2012; Badreddine, Blount and Quilter, 2022).
6) Finally, with regard to the context of this study, researchers agree that cultural differences have received too little attention in the study of online health. As such, the combination of Irish data and American data in this study contributes to research calls into health information concerns in both a European context and a cross cultural context (Bansal, Zahedi and Gefen, 2010; Anderson and Agarwal, 2011; Bélanger and Crossler, 2011; Dinesen *et al.*, 2016; Lowry, Dinev and Willison, 2017).

Topical: The issue of self-disclosure is topical and continues to be addressed in leading psychology, sociology, management and information systems journals. Meanwhile, the issue of self-disclosure in online contexts, particularly that of health, continues to gain considerable attention from a multitude of disciplines. With the advent of Covid-19 and the corresponding growth in the use of DHPs, researchers from different backgrounds are working to understand how and why users interact, behave and disclose in an online health context (Bogg and Milad, 2020; Rowe, Ngwenyama and Richet, 2020). These questions are examined in a wide range of academic literature, in various disciplines and from multiple perspectives. Examples can be found in the following academic journals: American Psychological Association (Bogg and Milad, 2020), BMC psychology (Herbert, El Bolock and Abdennadher, 2021), Frontiers in Psychology (Zhu, Jiang and Zhou, 2022), Cyberpsychology, Behaviour, and Social Networking (Nguyen, Bin and Campbell, 2012), Sociology of Health and Illness (Legido-Quigley, Mckee and Green, 2014), Journal of Applied Social Science (Atwood, 2021), International Journal of Sociology and Social Policy (Thanh and Tung, 2022), Qualitative Sociology (Au and Eyal, 2022), Health Information Management Journal (Walsh *et al.*, 2018; Afful-dadzie, Afful-dadzie and Egala, 2021; Crameri, Dam and Prior, 2022), International Journal of Information Management (Wang *et al.*, 2017), MIS Quarterly (Kohli and Tan, 2016; Bao, Meyer and Kirksey, 2020), Information Systems Journal (Fox and Connolly, 2018), European Journal of Information Systems (Lowry, Dinev and Willison, 2017), Computers in Human Behaviour (Hallam and Zanella, 2017), Journal of Medical Internet Research (Dinesen *et al.*, 2016), and Frontiers in Public Health (Yuchao, Ying and Liao, 2021). This diverse collection of academic publications looks at online health disclosure and communication, this serves as an indicator to the topical nature and societal importance of this current research study.

Benefits for future research: This research has both theoretical and practical value. It provides increased insights and offers empirical and theoretical contributions to I.S. literature that furthers our knowledge base with regard to the role of trust, privacy, culture, reciprocity, social influence and personality traits in the context of digital health disclosures. In doing so, this research elucidates the direction of key relationships, such as trust in health platforms (THP) and health information privacy concerns (HIPC), and their influence on disclosure behaviours in an online health context. These findings offer new avenues for future research to consider when exploring user interaction with key digital health infrastructure, an area that will garner increased research attention due to Covid-19 and the proliferation of DHPs.

Simultaneously, this research has commercial implications that provide actionable insights for health technology vendors, e-government and policy makers, and online behavioural psychologists who wish to foster more effective health disclosure environments online. It equips health technology vendors with a more sensitive understanding of what factors can influence user disclosure behaviour and informs policy makers on how to foster trustworthy platforms that can reduce health privacy concerns and therefore benefit public health initiatives. Finally, the research can assist online behavioural psychologists who wish develop informed psychological interventions via DHPs based on personality trait insights garnered from this study. As a result, this research offers a number of avenues for future health technology developments and public health interventions.

1.5 Methodology

In undertaking this research a pluralist methodological approach is used. The three main stages of the approach are:

(1) Theory building,

(2) Theory testing, and

(3) Theory refinement.

In the theory building stage of this research a review of the literature is conducted (chapter 2) and the existing theory and research on self-disclosure, trust and privacy risk beliefs from information systems, psychology and sociology disciplines is surveyed. The gaps in contemporary knowledge of the self-disclosure construct are observed and a number of conjectures that extend existing theory are developed.

The second phase of the research is theory testing. A pluralist approach was considered an appropriate and efficient approach to study self-disclosure in DHPs. The research therefore uses both surveys and stakeholder interviews. 151 quantitative surveys were completed by Irish participants and 154 quantitative surveys were completed by U.S. participants. Participants were all English speakers with previous experience of at least one DHP. Participants ranged from undergraduate and postgraduate students to employed/self-employed and retired. 20 follow-up qualitative interviews were conducted with survey participants, 10 from Ireland and 10 from the U.S. Interview participants were representative of the survey sample.

In the final phase of the research process, theory refinement, the research findings are reflected upon and compared with existing theory and with previous studies in this area. This results in a number of refinements being made to the initial model used in this research. These refinements can be used to advance our understanding of self-disclosure. Areas for future research are also outlined.

1.6 Dissertation structure

There are seven chapters in this dissertation. Chapters One to Three represent the first stage of the dissertation. In these chapters, the research problem, the relevance of the topic, the underlying literature, theory and research framework are outlined.

Chapter Two provides an overall view of the evolution of thought on various dimensions of the self-disclosure construct and a context in which to analyse the various approaches used by previous researchers. This is followed by a detailed review of the antecedents of online self-disclosure. Both trust and information privacy concerns are discussed, followed by a discussion on the underlying theoretical lens to be employed for this study.

Chapter Three outlines and justifies the philosophical stance and research design. The most appropriate research methodology to address the research questions is discussed and the choice of a pluralist approach to guide the research is justified. The chapter finishes with an overview of the research framework for this study.

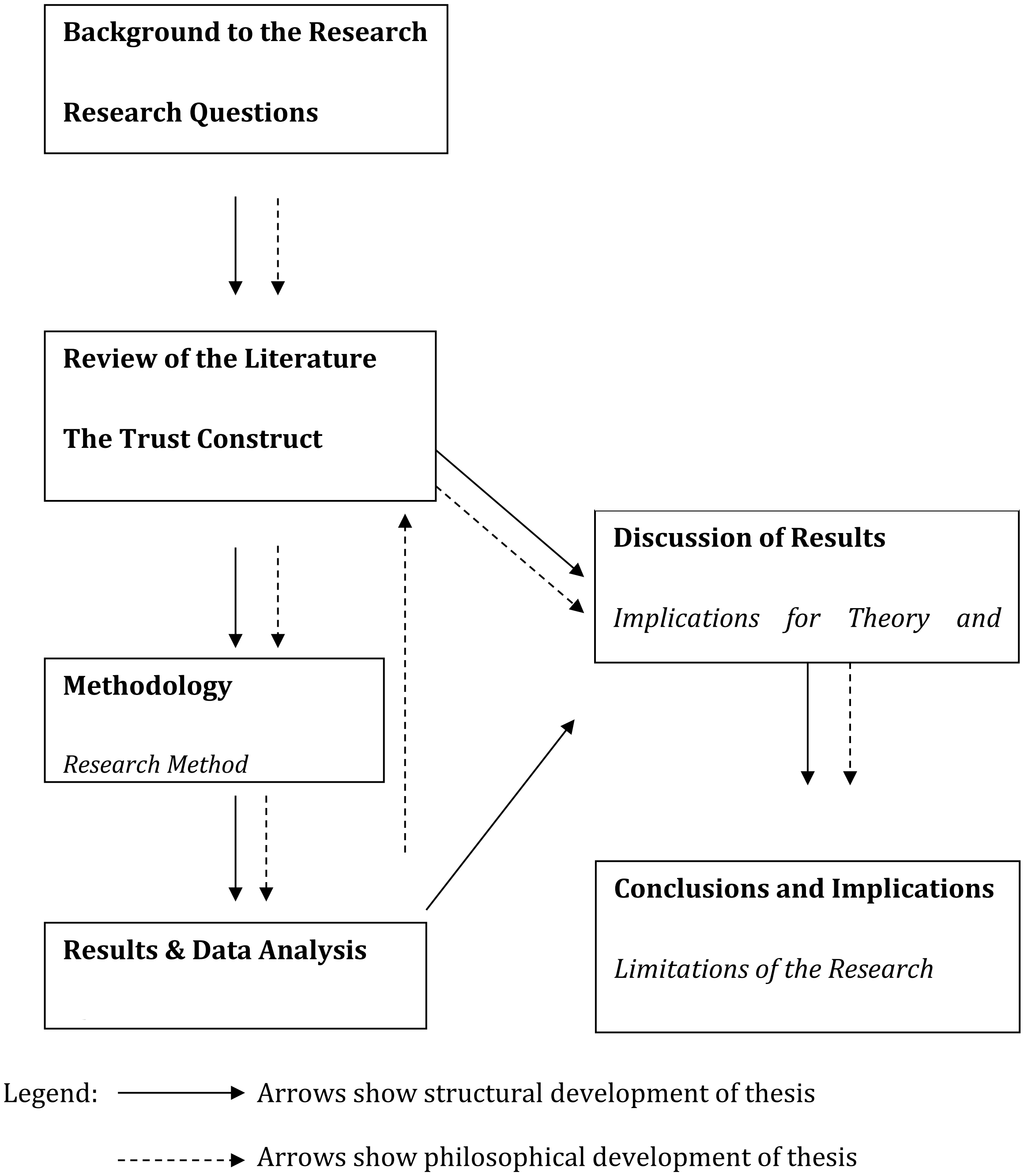
Chapter Four presents the results of the quantitative analysis from two surveys conducted in the U.S and Ireland.

Chapter Five presents the findings of the qualitative interviews. In this chapter the quantitative and qualitative findings are integrated and meta-inferences are developed.

Chapter Six presents the research contributions of the study, a revised framework and implications for practice. The results are also considered in the light of existing theory and previous studies in this area. Based on the research results, new theoretical propositions are advanced which result in modifications to the initial model used in this research. This modified model's contribution to theory and practice is then outlined

Chapter Seven concludes the dissertation with a summary of the claimed contribution of this study and a brief discussion of the limitations. Finally, areas for areas for future research are suggested. Figure 1.2 outlines the structure of the dissertation. Based on the structure proposed by Cronk (2003) it shows both the structural and philosophical development of the dissertation.

Figure 1.2 Dissertation Structure



2 Chapter Two: Literature Review

Self-disclosure: The act the of revealing personal or private information about one's self to other people **(APA, 2022).**

2.1 Introduction

The purpose of this research is to examine online self-disclosure in the context of digital health platforms, specifically to identity the antecedents of self-disclosure and the factors which shape their formation in Ireland and the United States. Self-disclosure has been important to researchers across a multitude of disciplines and generations leading to a lack of definitional consensus. This chapter therefore starts with an historical discussion of self-disclosure in section 2.2 followed by a definitional discussion of the construct in section 2.3. Following this, a brief review of the psychology, sociology and information systems literatures in terms of their examinations of self-disclosure and the knowledge which this reveals is provided.

This is followed (section 2.4) by a discussion of two key potential antecedents. Self-disclosure is a trust response which exists in a context of perceived risk. For that reason, the literature highlights two key antecedents which merit particular attention - the role of trust beliefs and risk beliefs. This research examines the effect of both in terms of their influence on self-disclosure of personal health information on these platforms. Moreover, factors which the literature indicates can shape both trust and privacy concerns, such as social influence and perceived reciprocity are also examined to determine their effect and role in generating a self-disclosure response. Theoretical frameworks which have been found helpful for understanding self-disclosure are discussed in section 2.5. The chapter concludes with a brief summary of the gaps identified through this review and a justification of hypotheses. The chapter structure is outlined in Figure 2.1.

Figure 2.1 Chapter Structure

2.2 Historical Roots of Self-Disclosure

As long as one person has been able to impart subjective experience to another, self-disclosure has existed as a phenomenon. Whether the first utterances of hunger from the first new-born to the first mother, or the broadcasting on Twitter of one's love for a recently purchased coffee, we as people have been participating in self-disclosure ab initio. Over time, the modes of self-disclosure have grown; a tattoo of allegiance; the crucifix around one's neck, a social media status update, sharing Fitbit steps, inputting credit card details for online transactions, transatlantic phone calls, and wearing of sensory health devices. Our self-disclosures can be conscious or unconscious, verbal and non-verbal, voluntary or solicited. We can self-disclose face to face, in an interpersonal relationship or via a computer mediated communication (CMC) with friends and strangers.

This phenomenon of self-disclosure has long been studied by psychologists and sociologists. In the early 20th century, Sigmund Freud developed the concept of the *'id,'* which he described as the primal, instinctual part of the human psyche. Freud believed that the id was responsible for our basic urges and desires, including the need for self-preservation (Hattangadi, 2021). As humans began to interact with others, Freud believed that the id would often come into conflict with the ego, which is the part of the psyche that is responsible for reality testing and decision-making. He believed that it was for the purpose of resolving these conflicts that humans engage in self-disclosure, which allows them to share their innermost desires and fears with others.

In the mid-20th century, psychologist Carl Rogers further advanced our understanding of self-disclosure through the development of his concept of *'unconditional positive regard,'* (Thorne, 1992). Rogers proposed that humans have a need to be accepted and valued by others, and that this need is often met through self-disclosure. He argued that this is because self-disclosure enables humans to form closer relationships with others, through the sharing of intimate details about themselves, which are accepted and validated by the other party.

One of the earliest empirical studies on self-disclosure in an online context was conducted by John Suler in 1996, who found that people self-disclosed online for a variety of reasons, including to make new friends, to express themselves, and to feel closer to others –consistent with Rogers perspective. Interestingly, Suler found that people were more likely to self-disclose in an online context if they felt anonymous and safe, pointing to an early recognition of risk and the importance of privacy for those who disclose in online contexts. Since then, the topic of online self-disclosure has gained sustained research attention, but the question as to how it is defined and operationalised, has not been comprehensively resolved. For example, early self-disclosure researchers, such as Jourard, (1971) and Wheeless and Grotz, (1977) posited that self-disclosure is the portrayal of the self to others and an attempt to express one's subjective experience to others, with an expectation of reciprocation. However, the world has changed radically over the past decades and many offline disclosure behaviours now translate to the online sphere. In recent years, there has been a growing trend of people sharing intimate details about themselves on social media platforms such as Facebook and Twitter. Today, people have multiple means of communication and digital platforms through which they have the opportunity to disclose personal information. For example, by 2024 it is estimated that over 700 million individuals will be wearing wearable health trackers such as Fitbit (Laricchia, 2022), which automate disclosure of health data. Personal experiences are disclosed by 299 million people on Twitter each day each (Kemp, 2022a). Similarly 1.9 billion people actively disclose and receive information from others on Facebook each day (Kemp, 2022b). Some researchers have argued that the trend towards higher levels of self-disclosure online is a result of the *'disinhibition effect,'* (Suler, 2004), which occurs when people feel less inhibited in online environments than they do in face-to-face interactions. Others have argued that the disinhibition effect is not the only factor that contributes to self-disclosure on social media and that anonymity, asynchronous communication and the desire to form closer relationships with others are also significant factors (Joinson *et al.*, 2010). What is incontrovertible is that online technologies afford new opportunities to disclose information and this creates opportunities for vendors seeking to increase use of their online platforms and seeking insight into their consumer bases. In parallel, these technologies and digital platforms empower individuals, creating direct information transfer pathways. This is particularly important in a context of reduced availability and access to medical resources in many regions due to economic limitations or travel restrictions. In such contexts, the benefits which such online platforms offer for those who disclose information for the purpose of receiving advice, as well as the opportunity for others with relevant experience to respond with appropriate guidance, cannot be underestimated. Therefore, insight into the factors motivating disclosure in an online context is not just interesting, but important (Tihanyi, 2020).

Defining self-disclosure is not a trivial undertaking, but is essential for its examination. A review of empirical research will find a number of definitions of self-disclosure some relating to offline interaction, some to online interactions. Despite all the definitions that are found and the varied modes of communication employed, there remains a common understanding that self-disclosure relates to the voluntary revelation of personal information to another, in the anticipation that reciprocation will occur and a relationship will develop over time (Jourard, 1971; Cozby, 1972; Altman and Taylor, 1973; Wheeless and Grotz, 1976; Joinson *et al.*, 2010; Posey *et al.*, 2010; Nguyen, Bin and Campbell, 2012).

2.3 Defining Self-Disclosure

The first recorded use of the term dates from the 1800s (Oxford, 2017) and has generally referred to the revelation of one's subjective experience (Jourard, 1971; Tamir and Mitchell, 2012). As communication technologies have grown there has been corresponding growth and variation in how self-disclosure is conceptualised across disciplines. For example, communications researchers such as Pearce and Sharp, (1973) emphasise intentionality, describing self-disclosure as individuals' voluntary and intentional revelations about themselves to others, in a face-to-face environment. Others psychology and communications researchers such as Greene, Derlega and Mathews, (2006) emphasise the role of revelation, describing self-disclosure as the revelation of one's feelings, thoughts and experiences to others.

The definitions of self-disclosure found in the psychology literature emphasise one person imparting experience to another person, and that this communication can be verbal and non-verbal. For example, psychologists such as Jourard, (1971) have described it as the portrayal of the self to others, whilst others (Tamir and Mitchell, 2012) consider it to be an attempt to express one's subjective experience to others. Similarly, Thibaut and Kelley, (1959) use this understanding of self-disclosure in their examination of social relations and include that self-disclosure is a dyadic phenomenon in which social interactions occur with anticipated repetition or reinforcement. This research was an extension of that carried out by Dashiell, (1935) and Lewin, (1947) who posited self-disclosure as an aspect of social interaction that has a dyadic nature and is perceived as a reciprocal affair. This understanding of self-disclosure as a dyadic relationship with anticipated reciprocation in communication represents the majority view in the discipline of psychology.

The sociological literature also focuses on self-disclosure as a process of sharing personal information about oneself with others (Altman and Taylor, 1973; Johnson and Dabbs, 1976). However, it tends to emphasise the underpinning social motivations for that sharing, noting that the decision to self-disclose is often based on the perceiver's motivation, which can range from the need for social support to the desire for self-promotion (Argyle and Dean, 1970).

Researchers from the Information Systems discipline, such as Posey *et al.,* (2010), conceptualise online self-disclosure as a form of digital communication relating to an individual imparting personal and private information. Because information systems research focuses on how technology shapes people and their social or organisational context, researchers from this discipline examine such disclosures in terms of how they effect a response via technology, such as the expectation of an intangible benefit or integration into a network (Brynjolfsson, 1994; Constant, Kiesler and Sproull, 1994; Jarvenpaa and Staples, 2000; Posey *et al.*, 2010). This semantic variation in how self-disclosure is defined reflects the differing disciplinary lens of researchers and the fact that while there is agreement that self-disclosure is the sharing or imparting or personal information, there are differing levels of emphasis on its benefits, the factors underpinning self-disclosure, and its potential consequents.

While many commercial and organisational IS studies (Posey *et al.*, 2010; Krasnova, Veltri and Günther, 2012; XI Chen, Pan and Guo, 2016) have continued to use the self-disclosure definitions first put forward by Jourard, (1971) and Wheeless and Grotz, (1977), the current study has adapted the historical definitions in order to reflect the unique nature of the information being disclosed. This study relates to personal health information shared via IS and digital platforms. Based on the above discussion the current study draws on the description of disclosure provided by the Mayo Clinic, (2022, online) to define self-disclosure as 'the voluntary revelation of personal health information: health and biographical data, thoughts, feelings and experiences'. This definition has been chosen as it incorporates the primary components of self-disclosure definitions found across the three academic disciplines discussed and also includes the specific nature of the data being examined in this study, health data (Jourard, 1958; Wheeless and Grotz, 1976; Posey and Ellis, 2007; Nguyen, Bin and Campbell, 2012; Mayo Clinic, 2022).

The attention which researchers across the Psychology, Sociology and Information Systems literatures have paid to self-disclosure and its value to the current study is now discussed in more detail.

2.3.1 Psychology

Self-disclosure has received considerable attention in the discipline of psychology. Early research focused on the benefits of disclosing personal information to others (Jourard, 1961; Cozby, 1972) and conceptualised it as a key component to forming and maintaining close relationships (Jourard, 1961). In fact, when discussing the importance of self-disclosure as a therapeutic exercise, Jourard, (1964) went as far as to imply that one cannot achieve the fullest personal development without finding the courage to honestly express oneself. Later research also emphasised benefits, showing that self-disclosure can lead to greater relationship satisfaction and closeness (Gilbert, 1976; Reis and Shaver, 1988), that it can increase trust and reduce conflict in relationships. This is because disclosing personal information can help people to feel more understood and can foster intimacy and mutuality in relationships (Sprecher, Treger and Wondra, 2012). It can also be a way of coping with stress or difficult life events, as by sharing experiences with others, one can gain support and feel less alone (Tam *et al.*, 2006; Martins *et al.*, 2012). Whilst, the psychology literature typically perceives self-disclosure as a gradual process that occurs over time, it notes that there are some situations (e.g., therapy, online dating) in which people are more likely to disclose personal information more quickly (Ollier-Malaterre, Rothbard and Berg, 2013; Ho, Hancock and Miner, 2018).

Although much attention has been paid to the benefits of self-disclosure, some psychologists have also noted that it has potential to result in negative consequences and have explored these potential costs, showing that it can lead to negative outcomes such as decreased satisfaction and increased conflict. Such negative outcomes may arise from social rejection following an intimate disclosure (Gilbert, 1976; Forest and Wood, 2012; Ollier-Malaterre, Rothbard and Berg, 2013). Other negative consequences for the discloser include feeling embarrassed, vulnerable or exposed (Reis & Shaver, 1988). Too much self-disclosure can lead to feeling overwhelmed (Ho, Hancock and Miner, 2018). In some cases, self-disclosure can also lead to conflict and misunderstandings (Chaudoir and Fisher, 2010).

Psychologists have paid attention to the reasons motivating the decision to disclose or withhold information about oneself, showing that it is often influenced by a variety of factors, including the nature of the relationship, the level of trust between the parties, and cultural norms (Cialdini, 2001). This is because, in general, people are more likely to self-disclose to people who they feel close to and trust. Additionally, it has been shown that people from collectivistic cultures (e.g., Asian cultures) tend to be more reserved in their self-disclosure than those from individualistic cultures (e.g., Western cultures) (Hofstede, 2011).

2.3.2 Sociology

The sociological literature on self-disclosure is extensive. Early work focused on the role of disclosure in dyadic relationships, with researchers examining how different types of information are shared between friends, romantic partners, and family members (Johnson and Dabbs, 1976; Thompson, Smith and Woods, 1980). More recent work has expanded the scope of self-disclosure research to include studies of disclosure in social groups as well as disclosure in digital contexts such as social media. For example Chan, (2021) found a positive relationship between online self-disclosure and well-being on social media networks. While Lei *et al.*, (2022) found postpartum mothers in China who self-disclose on social media may obtain social support from others online and therefore improve their depressive mood.

As is to be expected, this body of literature has found that self-disclosure plays a key role in the development and maintenance of social relationships, showing that people who disclose more personal information about themselves are perceived as more likable and trustworthy and they are more likely to establish closer relationships with others (Altman and Taylor, 1973; Thompson, Smith and Woods, 1980; Cheung, Lee and Chan, 2015). For that reason, it has been shown that self-disclosure can also have positive consequences for the discloser, such as increased self-esteem and feelings of social connectedness (Utz, 2015). However, some researchers within the sociology discipline have also started to focus on the potential downside to self-disclosure, noting that it can lead to decreased privacy and increased vulnerability to exploitation (Chan, 2021; Baker-Eveleth, Stone and Eveleth, 2022).

From a process perspective, the sociology literature echoes the view of many psychologists, emphasising the dyadic nature of the disclosure relationship and expression of experience (Johnson and Dabbs, 1976). For example, Cozby (1972) observes that self-disclosure contains within it an intrinsic expectation of reciprocity, whilst Argyle and Dean, (1965) perceive self-disclosure as a means of establishing a bond between two people and note that it is possible to assume that disclosure is an intimacy variable, much like personal space or eye-contact. However, the sociology literature also incorporates recognition of the effect of distance on disclosure outcomes. For example, historical sociological studies on self-disclosure, such as that by Altman & Taylor (1973) have shown that the distance relationship between two people sharing intimate information is an influencing factor in the amount to which one discloses. These researchers found that the depth and the amount one discloses can be influenced by physical distance, a factor that interestingly is removed in an online environment.

2.3.3 Information Systems

When compared to more established disciplines, the study of self-disclosure within the Information Systems (IS) literature is at a nascent stage. Much of what does exist tends to focus on self-disclosure from an ecommerce and organisational perspective (McLure Wasko and Faraj, 2005; Robinson, 2017). These studies include examinations of what influences online consumers and co-workers to self-disclosure online; what mediums do online consumers and co-workers use; what effect does information disclosure have on the agents involved (Jarvenpaa and Staples, 2001; McLure Wasko and Faraj, 2005; Posey and Ellis, 2007; Posey *et al.*, 2010; Robinson, 2017).

For example, McLure Wasko and Faraj, (2005) examined organisational knowledge systems in an attempt to understand why strangers disclosed information to co-workers, showing that individuals will disclosure in order to build their reputation.

Other researchers (Jarvenpaa and Staples, 2001; Posey and Ellis, 2007; Posey *et al.*, 2010) have examined the flow of knowledge within organisations and online communities, namely how the disclosure of information impacts an organisation and the individuals disclosing information. It appears that the embedded sharing of information and its reciprocation within an organisation fosters a culture of collaboration among colleagues. The same bodies of research have found that often people disclose within an organisation without an expectation of reciprocation, but rather to build ones perceived reputation or social capital within a given network (McLure Wasko and Faraj, 2005; Grabner-Kräuter and Bitter, 2015). For example, in their work Jarvenpaa and Staples, (2001) found that professionals often self-disclose on internal information systems not in order to experience reciprocation, but to rather capitalise on opportunities to build their reputation.

In recent years there has been rapid growth in the use of social media networks and online communities and as a consequence, some attention has shifted to incorporate examinations of user self-disclosure on these platforms, which has provided valuable insights to businesses (Kozinets, 2002; Robertshaw and Marr, 2006; Robinson, 2017). Such research has shown that self-disclosure by online consumers is associated with reciprocation, formation of networks and social capital, and further extends to expected discounts and offers from companies (Sidgman and Crompton, 2016). This emphasis on value is particularly important as the online context is characterised by a wider audience and when this is considered in the context of a health information exchange such as a user self-disclosing private health information online, there would be an expectation that other members of the health platform used will offer valuable health information in return.

As noted, much IS research on self-disclosure has had a predominantly commercial and organisational focus. However, self-disclosure in an online health context differs considerably in terms of information type, sensitivity and potential consequences, than would be the case for most commercial contexts. As a result, a growing number of research papers in the IS domain call for deeper understanding of the antecedents of self-disclosure in online health platforms (Anderson and Agarwal, 2011; Lowry, Dinev and Willison, 2017; Adjekum, Blasimme and Vayena, 2018).

The IS literature acknowledges that outcomes of self-disclosure in an online context can vary in valence. For example, both positive and negative consequents are acknowledged by Derlega *et al.*, (1993) who contend that self-disclosure can positively add to a person's social relationships, while conversely making an individual feel vulnerable and at risk. From a positive perspective, a broad body of research claims CMC can afford users an interaction experience that is in certain cases more socially desirable than that which would be experienced in a face to face scenario (Walther, 1996; Tidwell and Walther, 2002; XI Chen, Pan and Guo, 2016). For example, whilst communicating through social media platforms and websites may seem impersonal; it is possible that the anonymity of internet communication may in fact result in a perception that it is a safer and less judgmental environment, thereby actually promoting self-disclosure. Support for this view is provided by Joinson, (2001) which found that CMC resulted in higher levels of spontaneous self-disclosure than was the case for face-to-face communication. Similarly, researchers (such as Morahan-Martin and Schumacher, 2003; Stritzke, Nguyen and Durkin, 2004) have found that the various forms of communication that ICT facilitates such as anonymous contributions or community wide broadcasts allow for people at various positions on an extrovert-introvert scale to express themselves more effectively than would be the case in traditional offline environments.

However, a less positive perspective on self-disclosure is provided by Choi and Bazarova, 2015) whose work has shown that the semi-public nature of social media networks may result in a heightened perception of risk for some people, which in turn can negatively impact their likelihood to engage in self-disclosure behaviours. This perceived risk may be justified with researchers such as Kiesler, Siegel and McGuire, (1984) arguing that computer mediated communication (CMC) environments foster more hostile exchanges than would be observed in a parallel face to face communication context, with associated research pointing to the fact that individuals are less restrained when disclosing online and tend to exhibit anti-normative behaviour due to online disinhibition effect (Suler, 2004). This may be because researchers examining online versus offline self-disclosure have found that

CMC sometimes results in greater amounts of self-disclosure in a shorter period of time (Nguyen, Bin and Campbell, 2012; Ho, Hancock and Miner, 2018).

It is evident that many researchers have attempted to understand how online and offline disclosure levels differ and the differing nature of risks and benefits in both contexts. While some has found that the online context promotes greater self-disclosure (Joinson, 2001; Carballo-Diéguez *et al.*, 2006; Christofides, Muise and Desmarais, 2009) , others report greater face to face self-disclosure (Chan and Cheng, 2004; Wan and Chiou, 2006; Schiffrin *et al.*, 2010), whilst some others find no significant differences (Kiesler, Siegel and McGuire, 1984; Parks and Roberts, 1998; Buote *et al.*, 2007). Part of the explanation of these differing results may lie in their focus on online or offline context – and more specifically the attributes of that context - rather than on the actual disclosure behaviour. Consequently, there have been calls to refocus IS research away from a sole emphasis on the ICT artefact and to rather focus on the IS artefact of online self-disclosures (Whinston and Geng, 2004; Lee, Thomas and Baskerville, 2015; Lowry, Dinev and Willison, 2017). Understanding of IS artefacts, specifically the trust generation mechanisms and the vulnerability concerns associated with online self-disclosure of personal health information (Whinston and Geng, 2004; Lee, Thomas and Baskerville, 2015; Lowry, Dinev and Willison, 2017) are currently lacking. Both merit exploration if we are to fully develop our knowledge of the self-disclosure behavioural response, and the factors influencing its motivation. In fact, the absence of insight into the role of trust in relation to self-disclosure of health data in an online context is particularly concerning as trust has emerged as a consistently important predictor of behavioural outcomes in other contexts of perceived risk (Mayer, Davis and Schoorman, 1995). This is because trust is related to the cognitive process of weighing up intangible costs and benefits in order to decide if a person or platform is competent, reliable and benevolent (Mayer, Davis and Schoorman, 1995; Lankton, Mcknight and Tripp, 2015). As such, the more trustworthy a person finds a circumstance to be, the more likely it is they are to wilfully self-disclose sensitive information (Wheeless and Grotz, 1977). As the disclosure of personal and often sensitive information is fundamentally a decision made under a condition of risk, it is therefore unsurprising that the corresponding influence of trust on self-disclosure levels in non-health contexts has been repeatedly confirmed (Wheeless and Grotz, 1977; Joinson *et al.*, 2010; Posey *et al.*, 2010). However, health data has particular associated sensitivities and while research on a variety of face-to-face communications research suggests an integral role for trust in the self-disclosure process (Johnson and Dabbs, 1976; Wheeless and Grotz, 1977; Durand, 2010), there is a dearth of research exploring the contextual role of trust in online self-disclosures of health data. Therefore, whether and to what degree trust influences the individual's disclosure of health information in an online context remains a matter of speculation.

As previously noted, trust exists in a context of risk (Mayer, Davis and Schoorman, 1995). The fundamental risk associated with self-disclosure is one of loss of privacy. Self-disclosure of health data is particularly consequential as it may reveal sensitivities that the individual would prefer to remain private, but the benefits of gaining advice require disclosure. This is the despite the many risks associated with disclosing health information online (Malhotra, Kim and Agarwal, 2004). One of the primary concerns is the potential for unauthorized access to health information. Another concern is the possibility of secondary uses of health information. Another key concern is the potential for loss of control over one's personal health information. Research into the impact that the perceived risks associated with health information privacy concerns (HIPC) may have on self-disclosures of health data in an online context is at an early stage (Kohli and Tan, 2016) and there is a need for insight into whether and how they influence self-disclosures in an online context, including the pathway of their influence, their relationships with other variables which may influence such disclosures and the factors influencing their formation. Without such insights, our ability to address such concerns effectively in order to increase the possibility of disclosure. Is limited The following section discusses potential antecedents of self-disclosure in more detail.

2.4 Defining Digital Health Platforms

As previously stated digital health platforms (DHPs) have been defined as collections of applications and technologies used to support the delivery of healthcare and wellbeing services (ITU, 2017; Alharbi, 2021). However, as this definition encompasses a broad variety of technological solutions and as there is no one unified definition of this term it is necessary to provide definitional clarity as to what DHPs are in the context of this study.

DHPs, in the context of this study refers to online communities and wearable health technologies; advanced digital systems that leverage wearable devices to collect, analyse, and transmit health-related data. They serve as interactive interfaces that provide personalized health services to users (Brennan *et al.*, 2010; Bittner *et al.*, 2015; Lundell *et al.*, 2015; Frontera *et al.*, 2016; ITU, 2017; Alharbi, 2021).

These platforms are primarily driven by wearable technologies such as fitness trackers, heart rate monitors, ECG monitors, sleep trackers, and glucose monitors. Examples include devices like Fitbit, Apple Watch, or continuous glucose monitoring (CGM) systems used in diabetes management (Alfayez *et al.*, 2021; Alharbi, 2021; Ghose *et al.*, 2022).

These devices capture real-time physiological data, track health parameters continuously or at regular intervals, and use this data to provide actionable insights. The data can include parameters such as heart rate, steps, calories burned, sleep patterns, and more.

Similarly, a diabetes monitor, such as a continuous glucose monitor (CGM), can track a user's blood glucose levels in real-time. This data is then sent to a digital platform, where it can be analysed and used to provide feedback to the user (Dinesen *et al.*, 2016). This can help individuals with diabetes manage their condition more effectively by providing real-time feedback on their glucose levels and alerting them when their levels are too high or too low.

These DHPs can also integrate with other health applications or systems, allowing users to synchronize and access their health data in a consolidated manner (Vieira Silva *et al.*, 2022). They can provide personalised recommendations based on the data, promote healthier behaviours, and help users manage various aspects of their health and wellness.

Moreover, DHPs can facilitate remote patient monitoring, enabling healthcare providers to keep track of patients' health remotely, intervene timely when necessary, and provide more personalized care.

In the broader context, these platforms exemplify the increasing shift towards patient-centric healthcare, where individuals are empowered to manage their health proactively. With the increasing adoption of these technologies, they have the potential to revolutionize healthcare delivery, contribute to preventive healthcare, and bring about substantial cost savings in healthcare.

2.5 Antecedents to User Self-Disclosure in an Online Context

The literature shows that self-disclosure is a complex phenomenon, with a variety of antecedents that can affect the decision to disclose personal information, whether in an online or offline context. These include trust beliefs, perceived risk, reciprocity and social influence, as well as personality and culture (Altman and Taylor, 1973; Posey *et al.*, 2010; XI Chen, Pan and Guo, 2016). Each of these will now be discussed in terms of their relationship to self-disclosure.

2.5.1 Trust

The Oxford dictionary, (2016) defines trust as a firm belief in the reliability, truth, or ability of someone or something. It has been described as the glue that holds society together and the lubrication that makes it work more effectively (Newton and Zmerli, 2011). It has drawn the attention of researchers across a broad range of disciplines, each of which has its own particular emphasis, as reflected through its unique emphasis on differing antecedents and contexts. Importantly, researchers from the sociology discipline emphasise that the key to understanding trust in modern society is to recognise that its constructs can alter depending on particular environments and systems (Luhmann, 1988). Thus, Gambetta's (1988) sociological definition states:

> *Trust (or, symmetrically, distrust) is a particular level of the subjective probability with which an agent assesses that another agent or group of agents will perform a particular action, both before he can monitor such action (or independently of his capacity ever to be able to monitor it) and in a context in which it affects his own action. (Gambetta, 1988: 217).*

In psychology literature, trust is perceived as a concept that reduces risk and uncertainty with respect to the unknowable actions of others (Niu and Xin, 2009). Lane and Bachmann, (1998) regards trust as a set of calculations that weigh the cost and benefits of certain actions to either a trustee or trustor. From a societal perspective, Hofstede, (2011) note that trust is sensitive to culture and that such differences must not be ignored. They contend that trust is an essential component of any society and that without trust in institutions and specialists a society cannot survive.

Whilst differences exist in terms of how trust is conceptualised, a number of commonalities are also evident. These include an understanding that (1) trust is expressed in terms of positive expectation or belief; (2) that trust exists in a context of potential or perceived risk; and finally (3) it assumes a willingness to place oneself at risk (Gambetta, 1988; Mayer, Davis and Schoorman, 1995; Rousseau *et al.*, 1998; Jan Hofstede *et al.*, 2010).

While some researchers argue that humans attempt only to trust others humans (Friedman, Khan and Howe, 2000), there is a larger body of information systems literature that argues humans also attempt to trust technologies. For example, Sillence *et al.*, (2011) have shown that the establishment of trust plays an influential role in patient acceptance of health information from online sources. Similarly, Connolly and F. Bannister, (2007) have demonstrated the influential role trust plays in the relationship between an online retailer and a prospective ecommerce customer. Benbasat and Wang, (2005)have shown that trust influences user acceptance of recommendation systems, and adoption and usage of knowledge management systems (Thatcher *et al.*, 2011).

Trust and self-disclosure

There is a general consensus that there is a positive relationship between trust and self-disclosure (Wheeless and Grotz, 1977; Joinson *et al.*, 2010; Posey *et al.*, 2010). In particular, the observed relationship is one where as greater trust is perceived the amount and depth of self-disclosure increases over time (Altman and Taylor, 1973).

That being said, much of the research on the relationship between trust and self-disclosure have focused on offline analysis. While studies have examined the dynamics of the relationship from an online perspective (Joinson *et al.*, 2010; Posey *et al.*, 2010; Shih, Lai and Cheng, 2017) there exists a smaller body of research that explores the relationship from an online healthcare perspective, and particularly in an Irish user context. Previous studies have also shown trust to have a significant impact on technology acceptance, which in turn facilitates self-disclosure (Lankton, McKnight and Thatcher, 2014; Lankton, Mcknight and Tripp, 2015). For these reasons, the present study pays particular attention to the dynamics of the relationship between trust and self-disclosure in an online healthcare context.

2.6 Trust Dimensionality

Researchers consider that a perception of trustworthiness results from the perception of a number of characteristics (Barber, 1983; Covello and Peters, 1996). Many researchers have sought to identify those characteristics (e.g. Butler and Cantrell, 1984; Butler, 1991; Mayer, Davis and Schoorman, 1995; Peters, Covello and McCallum, 1997). However, as of yet, there is no agreement in the literature as to which or how many characteristics influence the creation of trust. Despite this lack of agreement, certain factors repeatedly surface. Early research (Hovland and

Weiss, 1951) indicates perceived expertise to be a prime factor influencing perception of trustworthiness. Lieberman, (1981) suggests that trust in fiduciary relationships is based on beliefs which derive from two characteristics - the trustee's perceived competence (i.e. ability) and perceived integrity. For Barber (1983) and Covello and Peters, (1996) perceptions of knowledge and expertise, openness and honesty, and concern and care constitute the key perceptions influencing formation of trusting beliefs. Later research by Sitkin and Weingart, (1995) emphasises competency, benevolence and value-based trust. For Mishra, (1996) trust is the result of attributes defined as competence, concern, openness, and reliability. An examination of the determinants of trust and credibility in the area of risk communication (Peters, Covello and McCallum, 1997) indicates that perceptions of trust and credibility are dependent on three factors. These factors are perceptions of knowledge and expertise; perceptions of openness and honesty; and perceptions of concern and care. These three factors are similar to the characteristics of ability, integrity and benevolence.

2.5.1.1 Trust in Technology-Mediated Contexts

In a technology-mediated environment, trust assumes even greater importance, particularly in reducing perceptions of risk and enabling more confident interaction behaviour. Whilst this effect has been shown repeatedly in the ecommerce literature (e.g. Connolly and B. Bannister, 2007; Connolly and F. Bannister, 2007; Palvia, 2009; Li, Sarathy and Xu, 2011) far less attention has been paid to examining trust in online health contexts. This is despite Bansal, Mariam and Gefen, (2016) showing that context can impact trusting behaviours. As such, ecommerce, technology adoption and trust literatures remain valuable sources of insights that are likely to be relevant to an online health context. For example, the dyadic nature of trust as proposed by Mayer, Davis and Schoorman, (1995), that of trustor and trustee, applies equally to an online health context. In fact, Porter and Donthu, (2008) have shown that the perceived trustworthiness of an online community can reduce perceived risk.

Contemporary literature clearly identifies an influential role for trust in the acceptance of technology but it does not elucidate what constitutes trust in the context of technological interactions. This absence of clarity has led to something of a dichotomy of approaches when considering the trust construct in the context of technological interactions. One approach is to measure trust in technology based on human-like trust constructs. That is, where attributes such as benevolence, integrity and ability are assessed (Benbasat and Wang, 2005). Such an approach also reflects the trust construct found in management literature (Mayer, Davis and Schoorman, 1995).

The second approach is to adopt a system-like trust construct when measuring trust in technology. This approach, discussed by McKnight *et al.*, (2011), measures attributes such as reliability, helpfulness and functionality. Some examples of empirical research have shown sound reasoning for selecting either a human-like or system-like construct of trust. In the case of Benbasat and Wang, (2005) a human-like trust construct was employed when assessing trust in technologies that utilise a voice and animation interface. While a system-like trust construct might be employed when assessing trust in a more limited input/out interface, (Mcknight *et al.*, 2011).

While two trust constructs in technology exist, it is not always obvious as to which of the two should be utilised. Lankton, Mcknight and Tripp, (2015), for example, notes that a researcher may employ the human-like trust construct and ask a respondent their perception of a technology's integrity even though a respondent may not believe that a technology can display integrity. Such a situation could arise if a researcher perceives a technology to be human-like while the technology might actually be system-like in its design. Thatcher *et al.*, (2011) and Lankton, Mcknight and Tripp, (2015) continue that the opposite can also be true. Where a respondent might be asked about their perception of a particular technology's functionality (system-like), the respondent might observe the technology from a perspective of competence (human-like). For these reasons it is important to understand the two most common trust construct's used in IS research. Moreover, a better understanding of the relationship between the two constructs is required, as both Thatcher *et al.*, (2011) and Lankton, Mcknight and Tripp, (2015) note, current literature does not elucidate whether contexts exist where the use of one of these constructs is optimal over the other.

2.5.1.2 Human-like trust and its sub dimensions

When measuring trust between people researchers usually use human-like trusting beliefs; integrity, benevolence and ability/competence, (Mayer, Davis and Schoorman, 1995; Lankton, Mcknight and Tripp, 2015). Integrity is a belief that a person is honest and adheres to a socially accepted set of principles. Benevolence is a belief that a person will be kind, that their actions are thoughtful and removed from ulterior motives. Ability or competence is the belief that a person has the skills and attributes required to carry through on actions they claim to be able to fulfil.

2.5.1.3 System-like trust and its sub dimensions

Lankton, Mcknight and Tripp, (2015), have synthesised previous research by Mcknight, Carter and Thatcher, (2011), to conceptualise system-like trust in technology as one that is constituted by reliability, functionality and helpfulness. These authors argue that these three attributes "are corollaries to, the human-like trust attributes of integrity, competence, and benevolence", (Lankton, Mcknight and Tripp, 2015: p.883). Reliability is viewed similar to integrity, and holds the belief that a technology will perform properly and without fail, (Mcknight *et al.*, 2011). Functionality is viewed similar to ability or competence and holds the belief that a technology is designed with the capabilities, features and functions to fulfil the task it was designed for, (Mcknight *et al.*, 2011). Helpfulness derives from the human-like quality of benevolence and holds that a technology is responsive and supportive to a user's needs, (Mcknight *et al.*, 2011).

Table 2.1 Trust in People versus Trust in Technology

	Trust in People	**Trust in Technology**
Contextual Condition	Risk, Uncertainty, Lack of total control	Risk, Uncertainty, Lack of total user control
Object of Dependence	People—in terms of moral agency and both volitional and non-volitional factors	Technologies—in terms of amoral and non-volitional factors only
Nature of the Trustor's Expectations (regarding the Object of Dependence)	1. Do things for you in a competent way. (ability [Mayer et al. 1995])	1. Demonstrate possession of the needed functionality to do a required task.
	2. Are caring and considerate of you; are benevolent towards you; possess the will and moral agency to help you when needed. (benevolence [Mayer et al. 1995])	2. Are able to provide you effective help when needed (e.g., through a help menu).
	3. Are consistent in 1.-2 above. (predictability [McKnight et al. 1998])	3. Operate reliably or consistently without failing.

2.5.1.4 Trust in Digital Health Platforms

Research on the factors that influence trust in DHPs is limited as much of the extant research has only focused on health websites (Sillence, Briggs, P. Harris, *et al.*, 2007; Fan *et al.*, 2010; Harris, Sillence and Briggs, 2011; Sillence, Hardy and Briggs, 2013; Lederman *et al.*, 2014; Connolly *et al.*, 2022), but there are a number of studies from the health domain that provide valuable direction. These include the work of Bernhardt and Felter, (2004) and Walther, Wang and Loh, (2004) which suggests that domain designations (.org, .com, .gov etc.) can affect a user's perception of trust in a health website. Their research suggests when it is possible one should opt for a top level domain for health information sites. Conversely, sites with a .com domain registration frequently elicited low credibility and trust due to findings that imply commercial self-interest of sponsors with regard to health websites. Those sites affiliated with educational entities are advised to invest in the .edu domain registration. Walther, Wang and Loh, (2004) also note that the presence of advertisement in .org domain registered sites can negatively affect a user's perception of trust in a health website.

A second factor that has potential to influence trust responses is information convergence across different sources. For example, Walther, Wang and Loh, (2004) found that information repetition and convergence elicited user trust in websites as users felt that they could validate information found across sources. Participants in this same study also remarked on the positive effect of finding health information offline, via a health professional and being able to corroborate such information on an online health information site. Metzger and Flanagin, (2013) echo this finding and contend that the credibility and trustworthiness of digital information is dependent on the availability of information across different sources and different mediums of communication. In line with this, information quality and perceived impartiality has also been shown (Harris et *al.,* 2012) to influence the individual's trust response, a finding that echoes the work of Metzger and Flanagin, (2013). Perceived information quality is likely to have significant importance in an online health community where there is greater dependency on accurate advice. Within such a context, indicators of competence assume greater importance. It is therefore unsurprising that research by Eysenbach and Köhler, (2002) of consumers of online health information found that domain registration, website design layout, and clear and professional writing can influence a user's perception of trust in health information websites. Similarly, Sillence *et al.*, (2011) staged model of trust emphasises the influential role that visual design, information credibility and personalisation play in users' decisions to trust health websites. The importance of credibility is unsurprising as it is consistent with the fundamentals of the patient-physician relationship, in which it is assumed that the physician will act with the best interests of the patient, as per the Hippocratic oath (Lasagna, 1964).

2.5.1.5 Trust and Platform Design

A number of varied platform and website design factors have been shown to influence trust in DHPs (Adjekum, Blasimme and Vayena, 2018). For example, professional layouts, images, advertisements, physical addresses, and navigation menus all contribute to ones perceived trust in a website. Walther, Wang and Loh, (2004) created a number of mock-up health websites to test the influence of top-level domains and advertisements on perceived trustworthiness of health websites.

The .org domain performed best against .com, .edu and .gov domains. Advertisements were shown to have a negative influence on .org sites but a positive influence on .com or .edu sites. Bernhardt and Felter, (2004), have shown that mothers seeking paediatric information tend to trust a DHP when an information source and image are presented, one participant noted "I think for me, psychologically, I like to see a person's face, see what they look like, just because it helps me to decide if I trust them or not", (Bernhardt and Felter, 2004:4).

Research by Rains and Karmikel, (2009) reveals that the inclusion of navigation menus and images on DHPs help to cultivate a professional perception of a DHP which has a positive effect on perceived trustworthiness of a DHP. Adjekum, Blasimme and Vayena, (2018), have shown that ease of use of a DHP, customization and interoperability to be kep generators of trust in DHPs. In contrast Sillence *et al.,* (2007) have presented research that argues DHP users place greater importance on content and information quality as opposed to design when evaluating trustworthiness of a DHP. This research is supported by Bliemel and Hassanein, (2007) who show design and functionality to only influence DHP satisfaction. While research exists as to the role DHP design plays in influencing trust there is need to empirically investigate it in the context users trusting DHPs.

A contemporary development in design principles that is likely to have considerable implications for digital platform design and trust going forward is the Privacy-by-design approach to technology development (Cavoukian, 2009). Privacy-by-design is a concept that promotes the inclusion of privacy into the design of platforms, services, and systems. It is based on the idea that privacy should be built into the design of a platform or system from the beginning, rather than as an afterthought

(Perera *et al.*, 2016). Privacy-by-design seeks to ensure that privacy is considered throughout the entire development process, from the initial conception of the product or system to its implementation and use. The goal of privacy-by-design is to ensure that user privacy is respected and protected, while still allowing the product or system to be effective and useful. It is a concept that has been gaining traction in recent years as organizations and governments strive to protect the personal data of their users and citizens (Hutton *et al.*, 2018).

The concept of Privacy-by-design is based on seven core principles: (1) Proactive not Reactive; (2) Privacy as the Default Setting; (3) Privacy Embedded into Design; (4) Full Functionality – Positive-Sum, not Zero-Sum; (5) End-to-End Security; (6) Visibility and Transparency; and (7) Respect for User Privacy. These principles are intended to ensure that privacy is considered throughout the entire lifecycle of a technology, from its conception to its deployment and use (Cavoukian, 2009; Perera *et al.*, 2016).

Organizations have faced a variety of challenges in implementing privacy by design, including the need to ensure that privacy by design solutions are compatible with existing systems and processes, and the need to ensure that staff are adequately trained and supported in their implementation of privacy by design (Klitou, 2014).

The implementation of design principles such as Privacy-by-design that are proactive in engaging with security and trust issues on digital platforms have the potential to bring a number of benefits to organizations, services and digital platforms. These benefits include improved user trust, increased compliance with data privacy regulations, and improved data security (Abeywickrama *et al.*, 2022)

2.5.1.6 Trust and Information Quality

Information quality is characterized by features that are related to accuracy, timeliness, completeness, relevance, and consistency (Metzger and Flanagin, 2013). When DHP users perceive a DHP to contain some of these characteristics the tendency is for the website to be deemed trustworthy (Delone and McLean, 2003; Adjekum, Blasimme and Vayena, 2018). Yi *et al.*, (2013) and Song and Zahedi (2007) have for example shown that DHPs containing understandable, reliable, professional, useful, unbiased and up-to-date information were perceived to obtain quality information, and in turn were considered to be trustworthy. Bernhardt and Felter (2004) also include information convergence to play a role in perceived information quality. In their study mothers would trust a DHP if the information appeared many times in many places; otherwise, the website is not providing valid information since "no one else is corroborating," (Bernhardt and Felter, 2004:4).

In contrast, there exists research that finds no link between trustworthiness and information quality, but that rather users placed trust in a DHP if it appeared to have structural quality (Rains and Karmikel, 2009). That is to say navigational features, design and response time were deemed trustworthy characteristics. When one considers the salient nature of health information and associated digital platforms further research is required so as to understand whether and what aspects of information quality might render a health platform trustworthy.

2.5.1.7 Trust and Perceived Reputation

Reputation refers the process of recognition development across time and involves repetition of interaction. It is particularly associated with process based trust (Luo, 2002). Historically it plays significant role in offline trustworthiness (Cialdini, 2001;

Kozinets, 2002). In qualitative studies by Sillence et al. (2006;2007) reputable offline brands and entities have been shown to carry their perceived offline trustworthiness into the online domain. Unsurprisingly those platforms operated by medical universities, doctors, federal entities and advocacy groups were the most trusted with regard to health information seeking, (Eysenbach and Kohler, 2002; Dutta-Bergman, 2003; Quintana et al, 2001). Insurance company platforms and e-commerce websites handling health information were regarded as the least trusted for online health information, (Bernhardt and Felter, 2004; Dutta-Bergmam, 2003). Adjekum, Blasimme and Vayena, (2018) have also found that DHP provider repuatation has a signficant role to play in perceived trustworthines of a DHP.

2.5.1.8 Trust and Health Technology Vendors

Health technology vendors provide essential products and services to users and healthcare organizations, and the trustworthiness of these vendors is critical to the success of these organizations and user health. Given the importance of trust in these relationships, it is surprising that there is relatively little research on trust in health technology vendor relationships (Xu, Le and Montague, 2014; Desjarlais *et al.*, 2015; Adjekum, Blasimme and Vayena, 2018).

Prior experience and familiarity with using vendors and their technology has been shown to have a favourable influence on people trying a new platform (Song and Zahedi, 2007; Bansal, Zahedi and Gefen, 2010; Kim, 2014). According to Song and Zahedi (2007) prior experience with vendors was significant in the formulation of user trust in health platforms, while Aiken and Boush, (2006) revealed that lack of experience using health platforms could also result in unwarranted trust being developed.

There are a number of other factors that contribute to trust in health technology vendors. One of the most important is the vendor's ability to provide quality products and services (Lankton, Mcknight and Tripp, 2015). Another important factor is the vendor's ability to keep their promises. Healthcare organizations need to be confident that health technology vendors will deliver on their commitments. This includes providing promised features, security and functionality, and resolving problems in a timely manner. The vendor's reputation is also a significant factor in trust. Healthcare organizations and users need to be confident that they are working with a reputable vendor who has a track record protecting personal data, for example (Kim and Park, 2012).

Finally, the vendor's relationship with other healthcare organizations can also contribute to trust. If a vendor has a good relationship with other healthcare organizations, it can be a sign that they are reliable and trustworthy (Montague, 2010).

The trust between users, healthcare organizations and health technology vendors is essential to the success of health technology projects. This trust can be built on a number of factors, including the vendor's ability to provide quality products and services, keep their promises, and maintain a good reputation.

Table 2.2 shows some of the factors influencing trust in an online context which are relevant to the current study.

2.5.1.9 Review of Trust in Digital Platform Contexts

Antecedent	Author(s)	Study Details	Findings	Gaps in Knowledge	Reason for Inclusion /Exclusion
Design	Adjekum, Blasimme and Vayena, (2018)	Review of elements of trust in digital systems	ease of use; usefulness; customizable design; interoperability; privacy all influence trust	The influence of design is unexplored in an Irish online health platform context	Design and its role in an Irish context need to be investigated
Information quality	Sillence et al., (2007)	Construct a staged model of trust in health platforms	Citizens perceptions of trust are positively influence by perceived information quality	The influence of information quality is unexplored in an Irish online health platform context	In light of online platform growth (Lowry, Dinev and Willison, 2017), the influence of information quality in an Irish online health platform context needs to be investigated
Perceived risk	Bansel, Zahedi and Gefen (2010)	Examine the role of personal dispositions on privacy concerns and trust in health platforms	Perceived risk of privacy had a negative impact of citizen self-disclosure of private health information	The impact of perceived risk upon perceived trust in health platforms has not been examined in an Irish context	As citizen are gradually open to greater online risks, the role of perceived risk and its impact on trust and disclosure must be investigated in an Irish context
Socio-demographics	Kim, (2016)	Examine how different demographics utilise	Cultural and age differences impact how users interaction	Cultural differences in the context of trust in health platforms, in	Previous research shows possible influence.

		the internet for health information	with online health platforms	Ireland, has not been explored	
Personality	Bansel, Zahedi and Gefen (2010)	Examine the role of personal dispositions on privacy concerns and trust in health platforms	People high in agreeableness were more inclined to trust health platforms	The role of personality and its impact on trust in health platforms has not be examined in an Irish context	There is growing spotlight on big five personality trait analysis, this study offers a timely opportunity to examine its role in an online health platform context
Perceived reputation	Sillence et al., (2007) Walther, Wang and Loh, (2004)	Construct a staged model of trust in health platforms Identify the role of domain designations and advertising of perceived trust in health websites .	Citizens perceptions of trust are positively influence by perceived reputation. Top level domain designations increased perceived trustworthiness. Advertisements had a negative impact.	The relationship between trust and perceived reputation in the context of online health platforms requires empirical investigation	There is a need to clarify reputation role in trust in the context of online health platforms
Health technology vendors	Song and Zahedi, (2007) Dinev *et al.*,(2016)	Understand the determinants of trust in DHPs	Prior experience with using online health platforms positively impacts perceived trust	The relationship between prior experience, trustworthiness and adoption of health platforms has not been explored in an Irish context	The influence of prior experience on trust and adoption of health platforms merits further study

Table 2.2 Review of Trust in Digital Platform Contexts

2.5.2 Risk Beliefs

Trust exists in a context of perceived risk (Mayer et al, 1995). Such perceived risk refers to the subjective belief of suffering a loss (Bauer, 1960; Rousseau *et al.*, 1998). If a trustor perceives uncertainty or lack of control over a scenario or system, then the trustor may deem themselves open to harm or risk (Mayer, Davis and Schoorman, 1995). Risk perceptions are contextually determined. For example, Karwatzki *et al.*, (2017) found that perceived risk inhibits interaction with information systems and, Smith, Dinev and Xu, (2011) have also shown that perceived risk can inhibit website use. This may be because of the diminishing effect which such risk has on trusting beliefs and the expression of trusting response. Support for this is provided by Yi *et al.*, (2013) who showed perceived risk to have a modest negative relationship to trust in health websites. Similarly, the work of Fox and Connolly, (2018) found an inverse relationship between perceived risk beliefs and trust in eHealth adoption.

2.5.2.1 Privacy Risk Beliefs

In an information based digital health platform, perceived risk relates less to the attributes of the online technology and more to the risk associated with information disclosure to an anonymous individual or groups of individuals. In an online information transfer context, these risk beliefs have been described as *'the expectation that a high potential for loss is associated with the release of personal information' to others in their electronic communities'* (Malhotra, Kim and Agarwal, 2004, p. 341). Despite people's desires for relationships and interaction, individuals are understandably reluctant to impart with personal, private information of any kind, and in particular to do so on a digital forum where that information can be read and shared by an unlimited audience, as well as leaving the contributor vulnerable on many different levels. In an online environment the question of data ownership, security and access management of datasets only adds to current and perceived privacy concerns. This risk evaluation is consistent with Gefen and Ridings, (2002) contention that individuals engage in interactions on the basis of expected, intangible benefits, where perceived benefits are evaluated against perceived costs. Indeed, this internal cost benefit analysis is similar to what individuals do when deciding to trust a new situation (Mayer, Davis and Schoorman, 1995; Thatcher *et al.*, 2011). Clearly, the evaluation of perceived risk is likely to vary according to the sensitivity of information being imparted and the potential consequences of disclosure. A number of studies argue that perceived risk belief is an antecedent to online trust and self-disclosure. For example, Bansel, Zahedi and Gefen (2010) have shown that privacy risk beliefs exert a negative influence on willingness to trust and disclose. The issue is complicated by the fact that research (Joinson *et al.*, 2010) has shown that while people do carry privacy concerns, this does not necessarily translate into privacy protection behaviours. This may be age related as one analysis of contemporary literature (Desjarlais *et al.*, 2015) found that older adolescents perceived online self-disclosure as less risky than younger adolescents.

While the relationship between generic risks beliefs and their likelihood to trust and self-disclose has been examined before (Altman and Taylor, 1973; Malhotra, Kim and Agarwal, 2004; Posey *et al.*, 2010) there is less of an understanding as to how ones generic privacy risk beliefs influence more specific privacy concerns in relation to personal health information. Added to this, current research into how risk belief impacts one's likelihood to trust and self-disclose in a digital health platform is limited. The role of privacy risk beliefs therefore merits a granular investigation within the context of this study.

2.5.2.2 Health Information Privacy Concerns

Developing an understanding of Health Information Privacy Concerns (HIPC) is a complex task and builds on previous examinations of general information privacy concerns. Indeed, much work has been undertaken to conceptualise just what information privacy concerns are in terms of dimensions and structure (Hong and Thong, 2013). As a complex construct, it has attracted a great deal of attention in IS and health informatics literature (D'Arcy, Hovav and Galletta, 2009; Bansal, Zahedi and Gefen, 2010; Anderson and Agarwal, 2011; Hwang *et al.*, 2012; Kordzadeh, Warren and Seifi, 2016; Hallam and Zanella, 2017; Lowry, Dinev and Willison, 2017). The construct is commonly understood as an individual's concerns regarding collection, use and dissemination of their personal data (Hong and Thong, 2013). Due to its complex nature no universal measure for privacy exists (Bélanger and Crossler, 2011) but some common sub-dimensions do arise: collection, unauthorised secondary use, improper access, errors, control and awareness (Hong and Thong, 2013; Fox and Connolly, 2018).

Previous research has utilised different measures when examining information privacy concern. The Concern for Information Privacy (CFIP) measure (H. J. Smith, Milberg and Burke, 1996) was used to examine privacy concerns on an organisational information practice level and incorporated four common dimensions: Collection, Unauthorised Secondary Use, Improper Access and Errors. The Internet User's Information Privacy Concerns (IUIPC) measure (Malhotra, Kim and Agarwal, 2004) was developed to understand individuals' concerns when using the internet and included collection, control and awareness in its dimensions. Hong and Thong, (2013), have combined CFIP and IUIPC to produce the Internet Privacy Concern (IPC) measure. This comprehensive measure includes: Collection, Unauthorised Secondary Use, Improper Access, Control, Awareness and Errors. Moving from the general online information privacy concern domain to the specific online HIPC domain is an important matter. If a user has concerns about sharing and trusting private health information their health and wellbeing could be in jeopardy. It is for this reason that a focus is now placed on a need for a more granular understanding of specific health privacy concerns. Previous research has attempted to measure health privacy concerns using a singular dimension and one item measures. For example, Chhanabhai and Holt, (2007) asked respondents '*Are you concerned for the confidentiality and privacy of your health records?'.* Similarly, other researchers have applied CFIP in a health context (Angst and Agarwal, 2009; Hwang *et al.*, 2012; Dinev *et al.*, 2016). However, the measure proposed by Hong and Thong (2013) not only comprehensively encapsulates the dimensionality of information privacy concerns, but has also been previously and successfully extended for use in an online m-health context (Fox and Connolly, 2018), where it was adapted to measure HIPC, and found to provide detailed insights in relation to trust formation and m-health adoption. For that reason, it is considered an appropriate and comprehensive measure of health information privacy concern for the current study. The following section defines the five dimensions of HIPC: (Collection, Unauthorised Secondary Use, Improper Access, Control, Errors and Awareness).

Collection of health data refers to concerns regarding how health entities collect and store personal information (Smith, Milberg and Burke, 1996; Angst and Agarwal,

2009) . With the proliferation of digital health platforms and electronic health records the importance of this practise is magnified due to the exponential growth of big data storage and the concerns that arise from this (Istepanian and Al-Anzi, 2018). Indeed, the European Union has taken the decision to implement union-wide standardised practices for databases containing sensitive information. The General Data Protection Regulation (GDPR) came into force on the 25th May 2018, replacing the previous data protection framework under the EU Data Protection Directive (Government of Ireland, 2018).

Unauthorised secondary use and improper access refer to entities not part of an initial data sharing agreement gaining access to health data and then taking nefarious actions with this data (D'Arcy, Hovav and Galletta, 2009; Lowry, Dinev and Willison, 2017). Recent global hacks and information leaks such as those relating to WikiLeaks (Assange, 2015), the NSA Prism program (Greenwald and MacAskill, 2013) and the HSE ransomware attack of 2021 (HSE, 2021) serve to highlight the severity of unauthorised secondary use.

Errors refers to the inability of health data storage entities to properly process, store and edit a dataset (H. J. Smith, Milberg and Burke, 1996; Angst and Agarwal, 2009). Research indicates (Montague and Perchonok, 2012) that error reduction would likely increase usage of health platforms.

Control refers to the ability for users to gains access to their personal health data and also to edit it. Current research claims that increased control would reduce perceived privacy risk (D'Arcy, Hovav and Galletta, 2009; Lowry, Dinev and Willison, 2017).

Finally, *awareness* relates to an individual's self-awareness and self-efficacy with regard to how organisations gain access to and uses citizen health data (Angst and Agarwal, 2009; D'Arcy, Hovav and Galletta, 2009; Lowry, Dinev and Willison, 2017).

While the HIPC measure is more nascent in its use it is deemed appropriate for the present study as it incorporates previously used items that have been rigorously tested. The HIPC measure has also been successfully utilised in a health context prior to this study. Due to the obvious complex nature of HIPC and its consequents on trust and self-disclosure, further investigation in the context of the present study is imperative.

2.5.3 Social Influence and Self Disclosure

Behavioural responses such as self-disclosure exists within a social context where one individual communicates to another or others. It is frequently imitative of the behaviour of referent others within the individual's social grouping and therefore subject to social influence. That imitative social influence has been described by Deutsch and Gerard, (1955) as the degree to which an individual's beliefs, attitudes and behaviours are influenced by those in their environment.

Recognising the influence of the social environment on behavioural outcomes is consistent with the Theory of Reasoned Action (Fishbein and Ajzen, 1975), which proposes that an individual will observe group norms and actions in order to formulate their behaviour and degree of engagement in a shared environment. Cialdini, (2001) has also shown that individuals will often replicate the actions of others in a shared environment; those more open to social influence have been shown to trust a social environment and to self-disclose more readily if those around them are also self-disclosing (Venkatesh, 2003). Some studies have examined the role of social influence on trust and self-disclosure for users of digital platforms. Shih, Lai and Cheng, (2017) have shown digital consumers in Taiwan to be subject to social influence by way of building dependency within an online group and that this in turn led to trust formation. Posey et al., (2010) also showed that office workers were influenced by the actions of co-workers to trust and participate in online self-disclosure. Research by Desjarlais *et al.*, (2015) also indicates that the online environment can have a positive impact on people deemed to lack social skills; in a CMC environment they positively disclose where otherwise they might not.

Social influence has been shown to have a role in online trust generation (Zhou and Li, 2014; Shih, Lai and Cheng, 2017; Adjekum, Blasimme and Vayena, 2018). While research into generic social influence online exists, to date there very little research that examines whether or not it plays a role in trust development on DHPs. Similarly, research (Youn and Shin, 2019)has shown a relationship between social influence and privacy concerns in an online context. This relationship has traditionally been strongly supported in the literature (Rokeach, 1968; Rosenberg, 1976). For example, Rokeach (1968) in his work on beliefs, attitudes and values, suggests that values guide evaluations, attitudes and actions regarding objects and situations. Similarly, economists such as Rosenberg (1976) acknowledge that technological innovations do not exist in exclusion and are subject to social influences. It is therefore all the more surprising that the relationship between social influence and HIPC has not been examined to date. Questions such as whether social influence alleviates health privacy concerns remain unanswered, as does the question of whether social influence increases trust in digital health platforms? Due to the critical nature of THP an investigation of the role of social influence on THP and HIPC is deemed critical to this study. In doing so, this study is one of a nascent few studies that have queried participants on social influence as it relates to trust and privacy in an online health information disclosure context.

2.5.4 Perceived Reciprocity and Self Disclosure

Communication requires two parties in order to be successful and reciprocity in communication has been shown to establish a trusting environment and be a key enabler of self-disclosure (Jourard, 1971; Posey *et al.*, 2010). Indeed, reciprocity is a fundamental behaviour in personal relationship development. For example, research has shown (Khalil, Zia and Abdallah, 2019) that when reciprocity is perceived to have occurred it helps to alleviate fears of vulnerability, allowing relationships to develop further, which as a result, drives deeper trust and further self-disclosure. In fact, Nowak and Sigmund, (2005) have established that reciprocal self-disclosure can actually build intimate trusting relationships that enhance social capital (Grabner-Kräuter and Bitter, 2015) and quality of life.

Neurological observations on people self-disclosing and experiencing reciprocation have shown to positively stimulate the brain's dopamine regulation system, leading to the assumption that there is a subconscious desire for repeat reciprocation over a disclosure period (Tamir and Mitchell, 2012). Other research shows that the more that reciprocal self-disclosure occurs over an extended period of time the more those interactions are likely to result in divulging of deeper, more intimate information thereby also indicating increased levels of trust (Altman and Taylor, 1973; Greene, Derlega and Mathews, 2006).

Contemporary research continues to link reciprocity with trust and self-disclosure, in that when an environment is perceived to be low in risk, deeper revelations occur and as reciprocation of revelation is experienced the intimacy of these revelations also grows in amount and depth (Posey and Ellis, 2007; Posey *et al.*, 2010; Tamir and Mitchell, 2012; Bansal and Gefen, 2015). Other research has also looked specifically at young adults finds that they are more willing to trust online platforms and disclose intimate information in a CMC environment than other age groups (Hollenbaugh and Everett, 2013; Jiang, Bazarova and Hancock, 2013). To date however there is a dearth of research that examines whether reciprocity has a role to play in online trust building on DHPs.

Similarly, recent research by Connolly *et al.*, (2022) indicates that the norm of reciprocity as evidenced through health community support and responsiveness can increase engagement and trusting responses within an online health community. While this assumes that the trusting response arising from perceived reciprocity reflects a reduction of perceived risk, this was not explicitly measured in their study and consequently merits more attention. However, other recent research by Zhang and Liu, (2022) shows that COVID-19 health information sharing in an online context stimulates further disclosure of information, thereby pointing to the influence of reciprocity. It also acknowledges that disclosure exists in a context of risk, indicating the need to for a more direct examination of the effect of reciprocity on privacy concerns in relation to disclosure. In doing so, this study is one of a nascent few studies that have queried participants on reciprocity as it relates to trust and privacy in an online health information disclosure context.

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2.5.5 Personality Traits and Self-Disclosure

People can differ considerably in their behavioural responses to the same stimuli and research (Nicholson et al., 2005) has indicated that personality may have important explanatory power in that regard., particularly in relation to evaluation of risk. For example, research (Rieger, Wang and Hens, 2015; Liu, Woo and Hon, 2016) has shown that personality traits and risk preferences vary and reflect the influence of social, cultural and economic environments.

Consideration of personality variables as a potential influence of offline self-disclosure is not new. For example, Jourard and Lasakow, (1958), developed an instrument to measure face to face self-disclosure and included personality as one of their six measures. In more recent years the role of personality traits and how they impact online self-disclosures is receiving new attention (Bansal, Mariam and Gefen, 2016; Xi Chen, Pan and Guo, 2016; Kim, 2018). Since the development of the "Big Five" personality traits (McCrae and Costa, 1997) a growing number of studies have tried to explain online trusting behaviours, self-disclosures and user impacts by using personality traits (Junglas and Johnson, 2008; Barnett *et al.*, 2015; Xi Chen, Pan and Guo, 2016; Pflügner *et al.*, 2021). These five traits are commonly referred to as openness, conscientiousness, extroversion, agreeableness and neuroticism.

- Openness reflects strong intellectual curiosity and a preference for novelty and variety.
- Conscientiousness refers to a desire to do a task well.
- Extroversion is reflected in a high degree of sociability, assertiveness, and talkativeness.
- Agreeableness refers to being helpful, cooperative, and sympathetic toward others.
- Neuroticism refers to the degree of emotional stability, impulse control, and anxiety.

In recent years the role of personality traits in online discourse and their ability to be manipulated has received much media attention. This is due in particular to the Cambridge Analytica scandal of 2018. Cambridge Analytica mined datasets of online user profiles from social networks and developed personality trait graphs on users in order to deliver targeted online messaging to users exhibiting particular traits. This was apparently done in an effort to influence citizen voting decisions during the Brexit referendum in Great Britain (Hinds, Williams and Joinson, 2020).

Analysis of the Big Five personality traits and whether they influence perceived health information sensitivity was carried out by Bansal, Zahedi and Gefen, (2010). The five traits were examined and according to results agreeableness was associated with higher levels of trust and disclosures, while the other traits exhibited no significance in trust formation and disclosures. The trait agreeableness relates to compassionate and emotional affiliation with others and has been shown to be higher in women (DeYoung, Quilty and Peterson, 2007). It is associated with respect and is present when relationships develop. Other research suggest that neuroticism and extroversion can impact online disclosure behaviour but this research is limited (Barnett *et al.*, 2015; Xi Chen, Pan and Guo, 2016; Kim, 2018).

Personality traits as antecedents is less explored in an online health context but recent events show that they are open to manipulation which can lead to societal impacts and dangers. Moreover, the digital platforms currently available to citizens have the ability to harvest data that could be used to develop personality graphs on its users (Moody, Galletta and Dunn, 2017; Büchi *et al.*, 2020) . Due to the sensitive nature of personal health data and the need to further develop our understanding of the role of personality traits in health disclosures it is deemed imperative to include a measure of the “Big Five” in this study. In doing so it is one of a nascent few studies that have queried participants on personality traits within a heath information disclosure study.

2.5.6 The Role of Culture

The role of culture has been acknowledged as influencing in studies that examine online self-disclosure (Posey *et al.*, 2010; Krasnova, Veltri and Günther, 2012). This research indicates that we cannot assume self-disclosure antecedents to be the same in all cultures. Indeed, researchers have called for cross-cultural examinations of online communication behaviours to be undertaken in order to elucidate the role of culture in such contexts as information disclosure online (Bansal, Zahedi and Gefen, 2010; Anderson and Agarwal, 2011; Bélanger and Crossler, 2011; Dinesen *et al.*, 2016; Lowry, Dinev and Willison, 2017).

As previously noted, risk preferences vary and reflect the influence of social, cultural and economic environments. (Liu *et al.*, 2016). Hofstede has described culture as: "…the collective programming of the mind that distinguishes the members of one group or category of people from others” (Hofstede, 2011:3). He suggested that cultural analysis should be segmented along six dimensions;

1. Power distance, which refers to tolerance for inequality where inequality is defined from below;
2. Uncertainty avoidance, which refers to tolerance of ambiguity;
3. Individualism vs. Collectivism. Individualism as a societal characteristic is opposite to collectivism and refers to degree to which people are integrated into groups. Individualistic cultures exhibit loose relationship ties while collectivist cultures exhibit deep integration from birth;

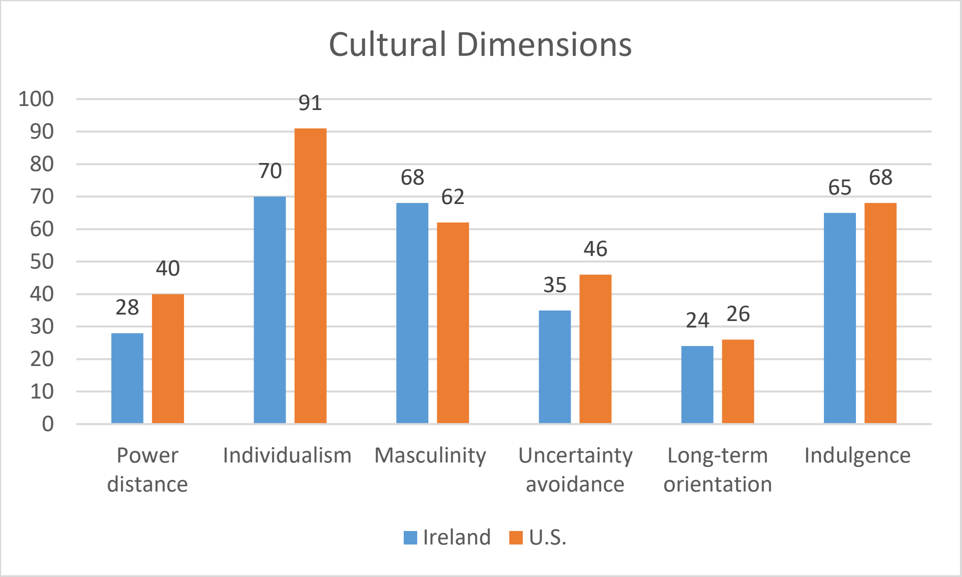
4. Masculinity vs. Femininity, which refers to the distribution of values between the genders.
5. Long-term vs. Short-term orientation, which refers to the focus of people's efforts: past, present or future;
6. Indulgence vs. Restraint, which refers to control tendencies with regard to desires and enjoying life.

Previous researchers have analysed cultures according to differing aggregations or levels (societal, national, gender, occupation). While analysing culture according to different aggregations may be attractive the analysis is always subject to transient changes. For example, if a person leaves a profession to undertake a different profession that person will likely soon exhibit some values associated with their new occupational culture. Hofstede therefore maintains that only at societal level can an intrinsic cultural analysis be conducted, as social cultures reside as somewhat unconscious values instilled from birth (Hofstede, 2011). From this basis Hofstede and those before him (Kluckhohn and Strodtbeck, 1961; Douglas, 2003) have posited the existence of two predominant cultures: individualistic and collectivistic cultures.

Many intercultural communication researchers consider that individualistic cultures are characterized by greater personal information self-disclosure than is the case for collectivistic cultures, which communicate more indirectly (Chen, 1995). However, a study undertaken by Durand, (2010) comparing self-disclosure in face to face and email communication between American and Chinese samples provided surprising results. The research found that Chinese participants reported disclosing more than American participants in both face to face and email contexts. Other studies (Posey *et al.*, 2010) also offer conflicting insights to the role of individualistic and collectivistic cultures, for this reason further exploration as to the role of culture in self-disclosure in an online health information context is required.

While the U.S. and Ireland are ranked similarly in terms of Hofstede's cultural dimension (see figure 2.2 below), there is a marked difference in citizen exposure to DHPs in both countries. Ireland is currently at the early stages of implementing a digital first health service ecosystem (Department of Health, 2017) whereas the U.S has a storied relationship with digital health initiatives (U.S. Centers for Medicare & Medicaid Services, 2020). These two countries have been selected as they are deemed a valuable contrast from which to gather insights for this study.

Figure 2.2 Cultural Dimensions



(source: Hofstede, 2022)

In the context of this study, culture refers to a complex system of shared values, norms, behaviours, beliefs, and practices that characterize a particular group of people, often aligned with their national or regional identity (Hofstede, 2011). Culture is a significant determinant of how individuals perceive and interact with the world around them, including how they engage with digital health platforms (DHPs).

Cultural attributes can significantly influence individuals' attitudes and behaviours regarding self-disclosure on DHPs (Posey *et al.*, 2010; Krasnova, Veltri and Günther, 2012). For example, societies with a collectivist culture, where group harmony and cohesion are highly valued, might encourage individuals to share their health information more freely for the perceived collective benefit. In contrast, societies with a more individualistic culture, where personal privacy and autonomy are emphasized, might see individuals being more cautious about disclosing personal health information on DHPs.

Cultural dimensions could also influence the level of trust and comfort individuals feel toward DHPs (Hofstede, 2011). For example, in societies with high uncertainty avoidance, people might be less willing to disclose personal health information due to fears of data misuse or breach of privacy.

Moreover, culture can also shape health beliefs and behaviours, which in turn can influence self-disclosure on DHPs. For instance, cultural beliefs about health and illness can impact what kind of health information individuals are willing to share, with whom, and in what context.

It's important to note that culture is not static but evolves over time under the influence of various factors, such as globalization, technological advancements, societal changes, and intercultural exchanges (Kluckhohn and Strodtbeck, 1961; Douglas, 2003; Hofstede, 2011). Therefore, cultural differences can also vary across different regions within the same country, reflecting local customs, traditions, dialects, policies, and historical experiences. In such cases, regional cultural differences need to be considered when examining self-disclosure behaviours on DHPs.

In conclusion, considering culture in the study of self-disclosure on DHPs provides a nuanced understanding of how cultural context shapes user behaviours, which can inform the design and implementation of culturally sensitive and inclusive DHPs.

2.5.7 Socio-demographics

Research shows that certain socio-demographic variables can play a role in citizen trust in health platforms, but there does not exists consensus findings on what variables these are (Xu, Le and Montague, 2014). Different studies show a role for age, education, health status, income level and cultural background (Brodie *et al.*, 2000; Dutta-Bergman, 2003; Lemire *et al.*, 2008; Adjekum, Blasimme and Vayena, 2018). Other research has shown that subsets within socio-demographics (young adults, adolescents, male, female, short term and long term studies) can differ in their importance (Desjarlais *et al.*, 2015).

2.5.7.1 Gender

The role and influence of gender on behavioural outcomes has long been explored in disciplines such as psychology (Carayon *et al.*, 2003; DeYoung, Quilty and Peterson, 2007). While numerous studies reveal influential roles for gender, there is more ambiguity in the results than there is consensus. Roberts, Walton and

Viechtbauer, (2006) have for example shown that when examining personality change over a short term gender is an insignificant predictor of change, but when examined over a long period of time gender plays a significant role in personality formation. Costa, Terracciano and McCrae, (2001) have also shown that gender can vary from significant to insignificant depending on cultural background. In similar fashion IS and health informatics literature reveals a lack of consensus on the role of gender. It has been examined through a number of lenses; privacy, trust and self-disclosure for example. The majority of the research carried out to date puts forward that females are more likely to self-disclose. The following table (2.3) is an overview of findings from the associated studies:

Study	**Context**	**Findings**		
		Women more likely to self-disclose	Men more likely to self-disclose	No statistical differences
Mickelson and Stevic, (1971)	Offline	X		
Cozby, (1972)	Offline	X		
Dolgin and Minowa, (1997)	Offline		X	
Joinson et al., (2010)	Online	X		
Posey et al.,(2010)	Online			X
Hwang *et al.*, (2012)	Online			X
Shih, Lai and Cheng, (2017)	Online			X

Table 2.3 Gender

These conflicting results make it difficult to determine its exact influence. For example, whilst some studies such as that of Dolgin and Minowa (1997) contend that females disclose more so than do males in amount and depth, the work of

Mickelson and Stevic, (1971) and Joinson et al., (2010) provides contradictory evidence. Parallel considerations such as whether female-female disclosure is higher than that of male-to-male remains undetermined. Similarly, whilst there is evidence (Papini et al., 1990) that disclosure content – e.g. the depth of disclosure and the difference between factual disclosure and emotional disclosure may vary according to gender, there is no empirical evidence to clarify whether and how that may apply in an online health context. Adding to the complexity is the fact that studies incorporating an examination of the influence of gender have focused on the offline face to face interaction context (Cozby, 1972), where gender and relationship to the target can be easily determined, unlike the online context where gender is either assumed or based on trusted self-reports. Consequently, whether gender increases or decreases online self-disclosure behaviour, particularly in an online health platform context remains undetermined and merits further investigation.

2.5.7.2 Age

Age is an important consideration that has potential to influence privacy concerns and outcomes such as self-disclosure of health information in an online context.

For the most part older demographics tend to be more reluctant to self-disclosure sensitive data if they perceive a risk (Janda & Fair, 2004; Joinson et al, 2010). However, these findings do not stand as conclusive evidence of the role of age in the disclosure of health information online. Studies carried out to date have tended to focus on ecommerce based disclosures (Chen et al., 2001) while a growing number of studies support health information research findings (Kordzadeh et al., 2016; Lowry et al., 2017).

Interestingly while the majority of studies found age to influence disclosure (Laric, Pitta and Katsanis, 2009; King, Brankovic and Gillard, 2012) its significance did vary across culture (Zhang et al., 2002), while in some studies it was found to have no significant influence (Posey *et al.*, 2010; Hwang *et al.*, 2012). Despite the variance in the role age is perceived to play in the question of online self-disclosure it is evidenced to have a role as shown in table X below. Due to the lack of clarity of its role it is deemed that further empirical examination is required to explore its influence.

The table 2.4 below illustrates these findings:

Study	**Context**	**Findings**	
		Age as an antecedent	No statistical difference
Janda and Fair, (2004)	Online	X	
Laric, Pitta and Katsanis, (2009)	Online	X	
Posey *et al.*, (2010)	Online		X
Joinson *et al.*, (2010)	Online	X	
Ji and Lieber, (2010)	Online	X	
Hwang *et al.*, (2012)	Online		X
King, Brankovic and Gillard, (2012)	Online	X	
Kordzadeh, Warren and Seifi, (2016)	Online	X	

Table 2.4 Age

2.5.7.3 Education

Education levels have received less attention with regard to online disclosure, as evidenced in the table 2.5 below:

Study	**Context**	**Findings**	
		Education: Significant differences	Education: No statistical difference
Chen *et al.,* (2001)	Online		X
Zhang *et al.,* (2002)	Online		X
Zukowski and Brown (2007)	Online	X	
Posey *et al.*, (2010)	Online		X
Hwang *et al.*, (2012)	Online		X

Table 2.5 Education

In their examination of internet users' privacy concerns, Zukowski and Brown, (2007) found that lower levels of education resulted in internet users being more likely to disclose personal information. Due to a clear lack of empirical investigation as to the degree to which education influences online disclosure it is evident that the issue merits further investigation.

2.5.7.4 Health Status

Contemporary research findings highlight that a citizen's health status, including morbidity awareness and emotional state do indeed influence disclosure of personal private health information.

Study	**Context**	**Findings**	
		Health status influences self-disclosure	No statistical difference
Flynn *et al.*, (2003)	Online	X	

Bansal, Zahedi and Gefen, (2010)	Online	X	
Anderson, Agarwal and Anderson, (2011)	Online	X	
Harris, Sillence and Briggs, (2011)	Online	X	
Montague and Perchonok, (2012)	Online	X	
van Heerden *et al.*, (2013)	Online	X	
Kordzadeh *et al.,* (2016)	Online	X	

Table 2.6 Health Status

William James, (1884) first posited that the act of personal interoception, to become aware of one's internal bodily condition and mental state, was the precursor to all self-perceptions and therefore subsequent actions. Lang, (1994) extends this to include that emotional states can be so varied that their influence on subsequent actions must be appreciated when conducting associated research. While the empirical evidence of health status as an antecedent is clear to see, the dynamic of this influence is not fully understood. Some research argues that health status is superseded by the intangible benefits offered as a result of information disclosure to a health platform (Angst and Agarwal, 2009). Other research (Harris, Sillence and Briggs, 2011) is more pointed, claiming for example that those suffering with chronic illness are more likely to forgo privacy concerns and disclose personal health information in the hope of positive reciprocation. This stance is supported by Kordzadeh, Warren and Seifi, (2016) who found citizens with poor health status are more likely to self-disclose in an effort to penetrate an online support network. Flynn *et al.*, (2003) found the opposite result, that those with poor health status exhibited a more guarded nature to self-disclosure, in addition Bansal, Zahedi and Gefen, (2010) reveal that the nature or sensitivity of an illness can negatively impact on one's levels of self-disclose of personal health information. The specific nature of an illness and its impact on self-disclosure is also highlighted by Anderson and Agarwal, (2011), Montague and Perchonok, (2012), van Heerden *et al.*, (2013) who present research that elucidates a lack of consideration for the influence of specific health status', emotional states and morbidity awareness across the field of IS and Medical Informatics research. As such there is need to explore further the influence of a citizen's health status on their self-disclosures of personal health information online.

2.5.8 Self-Disclosure: Measuring its Expression

Self-disclosure is a behavioural outcome and as such it can vary considerably in its expression. Much attention has therefore been paid to identifying how it can be expressed and how best to capture the elements of that expression.

A number of attempts have been made to identify measurable sub-dimensions of self-disclosure. One of the earliest attempts is that of Jourard and Lasakow, (1958), who set out an instrument to measure self-disclosure, the Self-Disclosure Inventory (SDI). The SDI consisted of six content areas (attitudes and opinions, tastes and interests, work and studies, money, personality, and body) and was limited to only exploring intimacy and honesty levels within these areas. The initial instrument consisted of 60 items (SDI-60) and was later revised to a 25 item instrument (SDI-25). While the SDI was applied throughout the 1960s and 1970s, a number of researchers found it to be lacking in predictive value.

On examining the SDI a number of other researchers attempted to build alternative instruments that had specific use cases: Self-Disclosure Inventory for Adolescents (West and Zingle, 1969), a scoring system for pre-adolescents (Vondracek and Vondracek, 1971), the Social Accessibility Scale (Rickers-Ovsiankina, 1956), Marshall's Self-Disclosure Questionnaire (1970), and a similar 144-item questionnaire used by Vondracek and Marshall, (1971). According to Wheeless and Grotz (1977) however they all displayed limited applicability and lack of utilisation, primarily due to instruments that were either too specific or that required intimate revelations from participants.

The development of an instrument that could be used in any scenario was required so that researchers could apply it across different contexts so as to create more universal interpretations of the nature of self-disclosure behaviours (Posey *et al.*, 2010). As noted, previous instruments required participants to reveal intimate information. As this is not always a desirable nor relevant feature, there arose a need for an instrument that could measure the intimacy level of a participant's disclosure without the participant having to give an intimate revelation, in effect protecting participant privacy. Consequently, Wheeless and Grotz (1976;1977) developed such an instrument based on two primary research goals: (1) what is the dimensional nature of reported self-disclosure and (2) what is the nature and strength of the relationships among dimensions of reported self-disclosure. The results found that self-disclosure is multidimensional with five measurable sub dimensions emerging; amount; depth; honesty; intent; valence.

Amount refers to whether a communicated disclosure of personal experience or information occurs frequently or infrequently and also to the duration of time over which it occurs. Contemporary research has shown that the advancement of a relationship is dependent on the amount of communication (Bansal, Zahedi and Gefen, 2010; Joinson *et al.*, 2010; Al-Saggaf and Nielsen, 2014).

Depth refers to whether or not a communication reaches a satisfactory degree of intimate revelation. Indeed, research reveals depth and intimacy to be integral to developing relationship closeness and penetration of a network (Altman and Taylor, 1973).

Honesty refers to the accuracy of the information being imparted in a disclosure. It is integral to the development of trust and reciprocation and can been seen to increase when a subject is submitted to the social influence of others (Deutsch and Gerard, 1955; Fishbein and Ajzen, 1975).

Intent refers to one's control and awareness of the information being communicated. Similar it is integral to the development of trust and therefore reciprocation. (Joinson *et al.*, 2010; Posey *et al.*, 2010; Wakefield, 2013).

Valence refers to whether there is a positive nature to the information bring imparted; is there an intrinsically positive message in a communication or an intrinsically negative message in a communication. This is central to the essence of self-disclosure and an individual that desires to fortify a relationship (Gefen and Ridings, 2002).

Self-disclosure has been viewed and measured along these five dimensions since Wheeless & Grotz, (1976) first published their work. During the preparation of this literature review over 20 studies spanning 30 years were found to have utilised these dimensions to effectively measure self-disclosure across various academic fields, both offline and online, such as Posey *et al.*, (2010) who examined disclosures in online work platforms. Due to their demonstrated contextual robustness and reliability, these sub-dimensions have also been chosen as measures of self-disclosure in this study.

2.5.9 Review of Self-Disclosure Antecedents

Antecedent	**Author(s)**	**Study Details**	**Findings**	**Gaps in Knowledge**	**Reason for Inclusion**
Gender	(Joinson, 2001)	Examines self-disclosure in a computer mediated environment	Women are more likely to self-disclose in a CMC environment	The influence of gender in European citizens is underexplored	Gender is widely supported in other contexts. There is a need to clarify the role of gender in the context of online health platforms
	(Shih, Lai and Cheng, 2017)	Examines online self-disclosure, in Taiwan, via constraint-based (lock-in) and dedication-based (trust-building) mechanisms and social identity theory	Gender did not have a significant influence on self-disclosure		
Age	(Hwang et al., 2012)	Examine privacy and disclosure habits of Taiwanese citizens regarding EHRs	Age did not significantly impact disclosure.	The influence of age on self-disclosure among European citizens has been underexplored.	Further research is required to understand the role of age on online self-disclosure, particularly with global age profiles rising
	(Kordzadeh, Warren and Seifi, 2016)	Exploration of behaviour on online health communities (U.S.)	Age had an impact on willingness to disclose		
Education	Posey et al., (2010)	Examine antecedents of online self-disclosure of office workers in UK & France	Education had no impact on self-disclosure	The influence of education on self-disclosure in an online healthcare context merits further examination	Research is required to examine the role of lower education levels on self-disclosure of sensitive information online
	(Zukowski and Brown, 2007)	Examines the influence of demographics on privacy on disclosure	Lower levels of education resulted in internet users having a higher propensity to disclose personal information		

Health Status	(Kordzadeh, Warren and Seifi, 2016)	See above	Poor health status resulted in willingness to disclose	The influence of health status on self-disclosure has not been fully explored in a European context	Empirical investigation is required as to the influence of health status on self-disclosure
	Van Heerden et al., (2013)	Collecting health information from HIV-positive women in S.Africa	The nature of an illness impacted self-disclosure		
Perceived Reciprocity	Posey et al., (2010)	Examine antecedents of online self-disclosure of office workers in UK & France	Perceived reciprocity increases online self-disclosure	The role of reciprocity in the context of online health platforms is unknown	Reciprocity is a fundamental component of self-disclosure. There is need to clarify its role in the context of online health platforms
	(Tamir and Mitchell, 2012)	Examine the neurological implications of self-disclosure	Individuals experience an intrinsic reward when self-disclosing and reciprocating	The role of reciprocity in the context of online health platforms is unknown	
	(Anderson, Agarwal and Anderson, 2011)	Examines the role of emotions in disclosure of personal health information	Lack of privacy & trust assurances in state entities inhibits disclosure and reciprocation	Lack of research examining the role of emotions in online self-disclosure and reciprocation	
THP	Posey et al., (2010)	See above	Perceived trust increases online self-disclosure	The role of trust and its influence on self-disclosure in the context of online health platforms is unknown	Trust is a fundamental component of self-disclosure. There is a need to clarify its influence on self-disclosure in the context of online health platforms
	(Joinson *et al.*, 2010)	Examines the role of trust and privacy in online self-disclosure	A compensatory interrelationship between trust and privacy	The relationship between trust and privacy in the context of online health platforms requires	

				empirical investigation	
Social Influence	(Shih, Lai and Cheng, 2017)	Examines online self-disclosure via constraint-based (lock-in) and dedication-based (trust-building) mechanisms and social identity theory	People are influenced to self-disclose by switching cost, dependency and cognitive trust		Empirical investigation is required to resolve the debate surrounding social influence and its role in online self-disclosure
	Posey et al., (2010)	Examine antecedents of online self-disclosure of office workers in UK & France via social exchange theory & social penetration theory	Social influence to use an online community contributes to online self-disclosure		
Risk beliefs	(Joinson *et al.*, 2010)	See above	See above	See above	Perceived privacy risk can inhibit self-disclosure. There is a need to clarify its influence on self-disclosure in the context of online health platforms
	(Wakefield, 2013)	Examines the roles of positive and negative affect on users' trust and privacy beliefs that relate to the online disclosure of personal information	There is an incongruity between users trust and privacy perceptions and their willingness to self-disclose online	The relationship between trust and privacy in the context of online health platforms requires empirical investigation	
Culture	Hofstede, 2011	The dimensionalizing of cultures in context	Different cultures exhibit different relationships with information disclosure	Cultural differences in the context of online self-disclosure of health information has not been explored	Conflicting research results merit further investigation as to the role of cultural dimensions on self-disclosure

HIPC	Fox and Connolly, 2018	This study focuses on mobile health technologies and the role of privacy in forging a mobile health digital divide	Older adults' perceived inability to use mobile health technologies due to mistrust, high risk perceptions, and strong desire for privacy	The role of HIPC and its influence on THP and self-disclosure in the context of online health platforms is limited	Privacy concern is a fundamental to trusting behaviours and self-disclosure. There is a need to clarify its influence on THP and self-disclosure in the context of online health platforms
Personality traits	(Barnett *et al.*, 2015)	Examines the role personality traits play in user adoption on technologies.	Conscientiousness, extraversion and neuroticism all impact technology usage.	Role of personality in technology adoption is under-researched.	Role of personality in online self-disclosure of health information requires examination

Table 2.7 Review of Self-Disclosure Antecedents

2.6 Theoretical Foundation of Research Framework

Theoretical frameworks can provide useful guidance and contextualization for understanding how a behavioural response such as self-disclosure is shaped, the factors which can shape the response and their inter-relationships. A number of competing theories that have potential to explain aspects of offline and online self-disclosure were considered. These are discussed in terms of their potential value to the current research. After the presentation of competing theories, the chosen theoretical foundation to the framework employed in this study is described.

2.6.1 Deindividuation Theory

Self-disclosure in an online context, such as that of a digital health platform, typically takes place in an anonymous group context and is subject to group dynamics which may influence the decision of whether and the nature of that disclosure response. Deindividuation theory provides some interesting insights in that regard. It is used to describe a psychological separation of the individual from others (Zimbardo, 1969; D'Arcy and Herath, 2011). It has been used to explain the actions of individuals within a group setting and originates from face to face communication studies. The theory puts forward that individuals within a group become unseen, that the anonymity afforded by a group setting creates a sense of de-individuation, whereby group members experience a reduction in self-observation, self-evaluation and concern for social comparison (Zimbardo, 1969; Christopherson, 2007). According to Christopherson, (2007) when deindividuation is observed in a group, individuals exhibit behaviours that are normally inhibited. This is due to a reduction of internalised controls such as guilt, fear and shame. In this situation individuals are said to lose sense of personal values and instead adopt group norms, a phenomenon sometimes referred to as 'mob rule' (Haines and Cheney Mann, 2011).

The theory of deindividuation is widely known as a result of the 1973 Stanford Prison Experiment (Haney, Banks and Zimbardo, 1973). The experiment, set as a role playing exercise, aimed to investigate how freely participants would integrate into the roles of prison guards and prisoners. Within hours both participant groups had conformed to their expected group dynamic; guards began to harass prisoners and prisoners began informing on bad behaviours of other prisoner to the guards. By the end of the experiment aggression by the guards had increased, they stripped prisoners and removed beds, while prisoners exhibited acute emotional disturbance. Even the researcher, Zimbardo was noted as displaying thought patterns akin to a prison superintendent as opposed to a research psychologist.

The Stanford Prison Experiment is an extreme representation of deindividuation and its implications on groups. In the context of information systems, deindividuation theory has been used to explore the effects of anonymity (D'Arcy and Herath, 2011; Haines and Cheney Mann, 2011). In particular, it has been utilised in an attempt explain online group conformity in an anonymous CMC environment. In one experiment (Haines and Cheney Mann, 2011), professional workers were observed using an anonymous chat room facility while making organisational decisions. Of significance, participant identity was anonymous, but participants' anonymous decision choices were broadcast to all participants. As a result, there was a significant relationship between availability of others opinions and group conformity.

Deindividuation theory has traditionally been associated with offline studies that attempt to explain why group norms develop with particular respect to anti-normative behaviour. In IS literature it has been used to explain group behaviour in an anonymous CMC environment. Research (Christopherson, 2007) has shown that it can also lead to normative group behaviour. While the characteristics of an online context can undoubtedly lead to deindividuation and the embracing of group norms (potentially increasing disclosure as a normative value), this theoretical framework does not focus on the other factors which can result in the decision to self -disclose, nor the fact that such disclosure is positive in orientation. Moreover, it has been used predominantly in an anonymous CMC context and as such is not deemed to hold value in a study that explores non-anonymised online health platforms.

2.6.2 Social Identity Model for Deindividuation Effects

Christopher Hitchens, (2010) once wrote that when contemplating the existence of both his personal political outlook and also the political outlook he disclosed during a negotiation or conversation, he realised he carried two books. The Social Identity Model for Deindividuation Effects (SIDE) proposes that we all carry two books: a personal book and a book which others perceive. That is to say that we carry two identities: a personal identity and a social identity (Christopherson, 2007) . The personal identity refers to unique individual, personal characteristics, while social identity refers to a basket of groups that an individual might belong to such as family, work, friends or religion wherein which aspects of the self are employed in accordance with the given context. As such, SIDE is context driven: if an individual is in a group circumstance where group norms are dominant, then an individual's social identity will operate, whilst not eliminating a sense of self. If group norm does not dominate, personal identity will operate (Postmes, Spears and Lea, 2000). In psychological literature SIDE has been successful in accounting for group behaviour in an anonymous and non-anonymous context. In particular, a meta-analysis of SIDE and deindividuation studies by Postmes and Spears, (1998) shows that SIDE does not support the traditionally held deindividuation theory presupposition that anonymity and reduced self-awareness cause anti-normative behaviour, exclusively. In fact, results were varied; rendering deindividuation devoid of merit if attempting to predict anti-normative behaviour in a group. The SIDE model suggests that deindividuation manipulations, such as the combination of anonymity, group unity (through matching clothes or behaviours) act to strengthen group salience and conformity to the associated group norms (Reicher, Spears and Postmes, 1995). This salience of the group identity associated with the norms is critical. Previous theories held that deindividuation led to disinhibited behaviour, whereas the SIDE model predicts conformity to salient group norms under deindividuated conditions.

SIDE has been used in CMC research. In studies relating to online communications and SIDE research (Postmes, Spears and Lea, 1998) it was found that CMC environments offer little variance in research findings when compared with face to face (FTF) findings, however the authors note that CMC is not neutral; social divisions from the offline world, or internal boundaries like social norms within a group prevail just as freely online as they do offline. This means therefore, that technology does have an influence on group dynamics. In one study Altschuller and Benbunan-Fich, (2013) aimed to understand if and how ad hoc online communities could develop trust over synchronous communications. The study found that when rehearsability (the extent to which users can reread and edit their messages before submitting them to the synchronous communication system) and partial electronic portrayal (only one form of true-to-life representation) was introduced trust was positively impacted, as was disclosure levels. Interestingly perceived trust and willingness to disclose declined as more and more personally identifiable revelations were made. Another study (Haines and Cheney Mann, 2011) contradicts the theoretical presupposition of SIDE. In this study participants in a CMC study did not display group consensus, despite group members being aware of each other's decisions. SIDE has been shown to useful in both offline and online environments, moreover it has shown to have implications for self-disclosure in CMC environments. However, as a theory it places a level of importance on anonymity and it has primarily been used for synchronous communications. Based on analysis of the historical application of SIDE it is more often used to assess deindividuation and the associated fallouts pertaining to group dynamics, therefore it will not be carried forward in this study.

2.6.3 Social Information Processing Theory

Social Information Processing (SIP) theory is a cue-based theory in which certain cues are deemed conducive to communication (Walther, 1992; Tidwell and Walther, 2002). In particular SIP is used to explain CMC information exchanges and argues that in the absence of nonverbal communication cues people will utilise alternative digital cues to replicate nonverbal cues as best possible. Unlike previous theories, SIP allows for asynchronous communication. In fact, it is more accommodating of the unique features of internet communications than other previously discussed theoretical frameworks. It proposes that, in a digital environment, people will engage in prolonged CMC, in similar fashion to face to face (FTF) communication, and that despite limited avenues to expression people will attempt to express the same amount and depth as would be the case in an FTF scenario. In fact, SIP claims that in the presence of sufficient time and a functional medium people will try to communicate just as they would in an offline environment. With regard to online disclosures, SIP argues that the absence of nonverbal cues can lead to increased disclosures. This is based on the assumption that in an effort to replace nonverbal FTF cues, people will over compensate with digital cues (Walther, 1992; Tidwell and Walther, 2002; Haines and Cheney Mann, 2011). That being said, Tidwell and Walther (2002) also note that further research is needed to properly account for the precise digital cues which create this response, and must also consider paralinguistic cues. CMC participants also ask basic questions, used as cues, that are normally observed in a FTF scenario, gender querying being an example. Also of note, SIP posits that CMC participants tend to ask intimate questions at a rate sooner than would be observed offline thus leading to intimate self-disclosures. This would support the SIP claim that paralinguistic cues and greater self-disclosures replace nonverbal cues and non-verbal disclosures (Nguyen, Bin and Campbell, 2012).

In a systematic review of offline and online self-disclosure (Nguyen, Bin and Campbell, 2012) SIP was shown to have predictive value with regard to greater self-disclosure frequency in online conversations. The same study showed support for SIP claims that CMC produces a disclosure frequency greater than that which is observed FTF, although the same analysis also provides no overwhelming support to any one CMC theory. While there is a body of research that has explored the effectiveness of SIP in an online and offline context – and its emphasis on cues would point to the role of trust generation mechanisms - it is worth noting that the majority of this research occurred more than 15 years ago and originated with one primary author (Walther, 1996; Tidwell and Walther, 2002; Walther and Parks, 2002; Walther, Loh and Granka, 2005). Moreover, SIP theory does not explicitly consider risk perceptions or how these may shape self-disclosure outcomes. Furthermore, it has insufficient utilisation in IS literature to warrant its usage in this present study.

2.6.4 Communication Privacy Management

Communication privacy management (CPM) theory was first discussed under a different name, that of communication boundary management, by Sandra Petronio in 1991. At its core CPM claims that disclosure is the process by which individuals give and/or receive private information. Within this process its claims there is a privacy boundary and that this boundary can grow as more people or entities become knowledgeable of private information. In doing so it brings with it a consideration for management and ownership of private information. That is to say that as more people or entities become aware of private information, the more this information is at risk and therefore privacy management is required (Petronio, 2002). As a result, CPM outlines three main components to manage private information: privacy ownership, privacy control, and privacy turbulence. Privacy ownership means people believe they own their private information. Privacy control represents the management process of providing or denying access to private disclosures. Privacy turbulence occurs when privacy rules break down for various reasons including purposeful violations and privacy rule mistakes, (Petronio, 2013).

CPM was initially used as a way to understand how two people in a relationship decided to disclose private information to each other (Petronio, 1991) and jas since been extended to a number of different contexts both offline and online. For example, Smith and Brunner, (2017) have used CPM when trying to understand why workers in multiple organisations and industries disclosed private information to co-workers and supervisors in an offline environment. In an online study context, McNealy and Mullis, (2019) have used CPM to understand the role of gender and culture when sharing information in an online gossip forum. Similarly, Posey *et al.*, (2010) utilised CPM when trying to understand how workers in two different countries disclose and manage knowledge on online work platforms. Of note, studies have also been using CPM in an effort to understand disclosures in a health context, with researchers such as Ngwenya, Farquhar and Ewing, (2016) using CPM when examining the process of information disclosure when patients have to share news of lung cancer with loved ones. Petronio, Helft and Child, (2013) have used CPM when attempting to understand the process a clinician goes through when having to disclose medical errors to patients. Indeed Petronio and Venetis, (2017) have provided a significant insight into CPMs use in healthcare across 11 countries and on topics from AIDs/HIV to cancer care and patient / provider disclosure management.

It is evident that CPM is applicable not only to online scenarios but also to a health information context. Moreover, it is apparent that CPM is of particular use when considering matters of information management after a disclosure has occurred. Although this study has a primary focus on factors that influence disclosures it does also take into consideration citizen privacy concerns and matters relating to data management. For this reasons this framework includes CPM to help ground the conceptual model and explain the information management process.

2.6.5 Social Exchange Theory

Social Exchange Theory (SET) (Thibaut and Kelley, 1959) views a social relationship as economic exchanges where individuals engage in social interaction after analysing and weighing the costs (for example, the loss of social independence or privacy) and rewards (for example, companionship, affection, or social support) of the relationship. SET provides a relationship foundation for the self-disclosure model used in this study.

SET (Thibaut and Kelley, 1959) is one of the oldest theories of social behaviour, which describes the process of interpersonal relationship formation and development. As stated, SET posits that social relationships are similar to economic relationships, where individuals decide whether to pursue or avoid a particular relationship after reviewing and weighing its rewards (benefits) and costs (risks). Relationship rewards refer to the benefits and support that individuals gain by developing the relationship, including companionship, affection, social support, or task-related benefits. Relationship costs, on the other hand, refer to the relationship's negative elements, such as the loss of social independence or privacy concerns (Luo, 2002). Where the perceived risks outweigh the benefits, the relationship is normally terminated. The current study does focus on the cost element associated with SET, in this case loss of privacy, but it does not conduct that examination from the perspective of mutuality of exchange. For that reason, while SET, through its recognition of how costs, such as privacy loss, can influence behavioural outcomes, provides important insights, the overall guidance which it affords this study is bounded. However, it does provide an important foundation for another theoretical framework, that of social penetration theory.

2.6.6 Social Penetration Theory

When applied to self-disclosure and the development of deeper relationships, SET gave rise to social penetration theory (SPT) which explains how self-disclosure grows with deepening relationships between individuals (Altman and Taylor, 1973). In accordance with SET, SPT proposes that individuals decide to disclose more information with others when they perceive more benefits and less cost in doing so.

SPT borrows the SET concept to investigate the influences and motivations of self-disclosure in relation to interpersonal relationships during the process of social penetration. In particular, SPT suggests that the perceived outcomes of any interpersonal relationship will play a significant role in motivating or demotivating self-disclosure. If an interaction is deemed safe, pleasant and useful, more self-disclosure is expected. If it is considered risky on the other hand the relationship will be evaluated according to its costs rather than its rewards or benefits.

As a consequence, SPT is integral to relationship development and deep self-disclosure (Altman and Taylor, 1973). Previous uses of SPT have included the observation of individuals, partners, perceived outcomes and situational analysis. As such, SPT refers to the intimacy of behaviours, thoughts and actions that occur prior to, during and after an interaction. Relationships are then noted by the degree of social penetration.

According to research (Thibaut and Kelley, 1959; Altman and Taylor, 1973; Johnson and Dabbs, 1976) there are three primary assumptions associated with SPT. *The first* is that relationships develop from a non-intimate state to an intimate state. This is determined by the reduction of perceived risk, a central component of the current study. According to Altman & Taylor (1973), as time progresses and perceived risk reduces, people in continued interaction develop rhythm and an ease that lends to greater depth and amount of revelations and disclosures. The passage of time allows for nuances to take ground, where partners engaged in an exchange can develop an almost private understanding of each other. Depending on the degree of social penetration between two partners, an exchange can develop into a flow like state akin to the Japanese concept of *'reading the air'* (Vogel, 2012) where there is a fluid understanding of both verbal and non-verbal communication channels. Repetition of physical, emotional and cognitive behaviours becomes apparent and there is a reduction in hesitant communication, reflecting increased levels of trust. As social penetration increases so too does the intimacy and range of personal disclosures, on both a verbal and non-verbal basis. In this way, SPT recognises the importance of trust, a factor central to the current study, and the reciprocal relationship between perceived risk and trust beliefs.

The second assumption associated with SPT is that individuals in an exchange will perform a cognitive cost-benefit analysis of the exchange across a timeline: past, present and future. The results of this analysis will determine the rate of relationship development and level of intimacy. It is posited by researchers (Jourard, 1971; Altman & Taylor,1973; Johnson and Dabbs, 1976) that this systematic approach to cost benefit analysis helps to alleviate the risk of revealing sensitive and personal information too soon into an exchange. As such intimacy development is viewed as a systematic output. This again reflects the cost-benefit aspect associated with risk evaluation, specifically information privacy concerns, as a rationally evaluated cost of self-disclosure in an online context. Again, this is particularly relevant to the current model and its emphasis on HIPC.

The third assumption of SPT is that just as social exchanges can grow from the non-intimate to the intimate, they can also exhibit a depenetration, moving from the intimate to the non-intimate. This dissolution of a relationship is exhibited by hesitated communications and decreases in levels of self-disclosure. In this way, SPT recognises the fluid nature of social exchanges in a digital health context cannot be assumed to automatically result in a positive behavioural outcomes, and in fact may result in outcomes which mitigate against such self-disclosure. It thus recognises that social exchange in differing contexts (including that of digital health platforms) may result in varying outcomes.

Social penetration theory was developed to provide a framework that would explain the development of relationships over time with particular attention paid to depth and amount of disclosures as intimacy increased. Historical application of the theory has shown support for SPT (Colson, 1968; Altman and Taylor, 1973) but its application in contemporary settings particularly online in CMC is less explored. More specifically there is a gap in the research that focuses on SPT and the assumption of a cognitive cost-benefit analysis over time when a computer mediated communication environment is in question. A study by Valkenburg and Peter, (2007), provides support for SPT in a CMC context. In this study, Dutch adolescents completed surveys about depth and amount of online disclosures, online behaviours and online interactions with both strangers and friends. The study revealed a positive correlation between closeness and perceived online depth of communication with strangers and friends. Of note, there was a significant correlation between frequency and duration of online exchanges when paired with amount and depth of disclosures in the case of friends interacting. These results lend support to SPT as Altman and Taylor (1973) had previously posited that time spent communicating should increase intimacy, and in that study, the depth and amount of online disclosures did increase.

The work of Posey *et al*., (2010) offers additional contemporary support for the value of SPT as a theoretical guiding framework for understanding disclosure in an online context. These researchers, examined self-disclosure of French and British working professionals, paying particular attention to online reciprocity behaviour, propensity to trust online communities, privacy risk beliefs, social influences and cultural conditions. The findings revealed significant roles for trust, reciprocity, privacy risk beliefs, social influence and cultural collectivism with respect to the amount and depth of online self-disclosure that occurred. SPT posits that individuals will self-disclose at greater levels when relationships are intimate and there is a perceived reduction in risk (Altman & Taylor, 1973). The findings of Posey *et al*., (2010) demonstrate that trustworthy environments where individuals feel safe can foster a greater level of disclosure and reciprocation of disclosures across time. Moreover, cultural conditions (collectivism Vs. Individualism) were shown to have an impact on levels of self-disclosure, while anonymity was shown not to be significant.

SPT is moderated by a number of factors that impact on levels of self-disclosure, such as closeness and environment. Individuals self-disclose at varying degrees of intimacy in order to extract benefit from an exchange. Whether in a face to face (FTF) situation or a CMC environment people have been shown to employ a systematic approach to the degree to which they self-disclosure. This cost-benefit analysis takes into consideration anonymity, frequency of reward, environmental conditions and emotional contexts (Altman & Taylor, 1973). As such the prevalence of CMC environments and their nature may expedite the cognitive cost-benefit analysis one undertakes.

While research exists that uses SPT to understand online self-disclosures, there is currently a dearth of research that has used SPT as a way to understand online self-disclosures in a health context. Given SPTs successful application in previous self-disclosure studies, its guiding association with SET and its recognition of constructs important this research (including perceived risks and trust outcomes), as well as its potential to guide examination of a digital health context, it is therefore deemed the most suitable underpinning framework to guide the current study.

2.6.7 Summary and Implications for this Thesis

The value of the above discussion relates to the fact that these theoretical frameworks provide insight into the factors and dynamics that merit consideration when examining how a self-disclosure response is shaped. The unique nature of digital health platforms means that they are characterized by particular vulnerabilities, specifically the disclosure of personal health information represents privacy loss. Self-disclosure therefore becomes a trust response resulting from a risk-benefit calculus and is a communication response that can vary in depth, dependent on the nature and outcomes of that calculus. SPT, through its recognition of these factors and dynamics, represents an important theoretical scaffolding for guiding this study. It emphasizes that individuals are more willing to engage in a relationship when the perceived benefits outweigh the perceived costs, thus creating a foundation for further relationship development. It posits that people assess interpersonal rewards and costs associated with their interaction with others, and that the advancement of the relationship is heavily dependent on the amount and nature of those rewards and costs (Altman & Taylor, 1973). To date research has shown the value of SPT as a guiding framework in an online environment and its application in a digital health platform research context will further confirm that value.

Finally, research has shown that communication norms are heavily influenced by culture (Horton and Spieler, 2007; Hofstede, 2011). Researchers including Posey *et al.*, (2010), Trepte *et al.*, (2017) Li, Rho and Kobsa, (2022) have shown that members of different cultural groups exhibit differing disclosure behaviours, namely that individualistic cultures tend to disclose more often. However, this was not in relation to disclosure of health data. While some research has focused on people's privacy concerns regarding online health data in specific national contexts (Hwang *et al.*, 2012; Kordzadeh, Warren and Seifi, 2016), and found health status, age and previous experience with health technology to influence privacy concerns and disclosure, no research to date has provided a cross-cultural examination of the factors influencing health information disclosure in DHPs. Therefore, whether differences in relation to the factors motivating such disclosure are culturally motivated remains a matter of speculation.

2.7 Summary of Gaps in Knowledge

When the above discussion into the nature of online self-disclosure is considered, a number of observations become salient:

Antecedents of self-disclosure on DHPs: The underlying antecedents of self-disclosure – and their inter-relationships - in an online health context remain underexplored (Nguyen, Bin and Campbell, 2012; Wang and Midha, 2012; Hallam and Zanella, 2017; Lowry, Dinev and Willison, 2017; Davazdahemami *et al.*, 2020; Yuchao, Ying and Liao, 2021). Moreover, while individuals' *intentions* in an online health context have received much attention (Anderson and Agarwal, 2011; Fox and Connolly, 2018), there remains a dearth of research that examines actual online *behavioral responses* pertaining to health (Anderson and Agarwal, 2011; Dinesen *et al.*, 2016). This present research therefore offers to bridge this gap through its examination of online health disclosure as a behavioral response (Faries, 2016).

THP and self-disclosure: How trust in an online health context is generated and how it influences self-disclosure is matter of speculation that requires more detailed attention (Vega, Montague and DeHart, 2010; Vega, Montague and Dehart, 2011; Fox and Connolly, 2018). Research on trust to date in the context of self-disclosure in an online health context is not only limited, but what does exist has operationalized the construct in terms of general trust beliefs, assumed a linear direct relationship with self-disclosure that has ignored factors and inter-relationships which might influence generation of trust in this context (e.g., Posey *et al.*, 2010).

HIPC and self-disclosure: The literature highlights the necessity of understanding privacy in a digital health context, in particular how privacy concerns are generated in this context and how these concerns influence trust and disclosure behaviours (as opposed to disclosure intentions) (Angst and Agarwal, 2009; Anderson and Agarwal, 2011; Lowry, Dinev and Willison, 2017). However, much research has focused on general privacy concerns, not considered how these relate to more specific health information privacy concerns and how this shapes self-disclosure of personal health information in an online context.

Reciprocity and social influence: There is a lack of understanding as to what role reciprocity and social influence play in the generation of trust and privacy concerns in an online health context (Alaqra and Wästlund, 2019; Khalil, Zia and Abdallah, 2019). Moreover, research which has examined self-disclosure in an online employment context has conceptualised both reciprocity and social influence as having direct linear relationships with self-disclosure, ignoring potential relationships and their more nuanced effect on behavioural outcome. This has limited our understanding of the effect of these constructs and is not consistent with theoretical frameworks (such as Theory of Planned Behaviour (Venkatesh *et al.*, 2003)) which have repeatedly shown that the influence of normative factors on outcome is not directly expressed. This research helps to clarify the role of both of these constructs and how they are expressed via the research framework employed in this study.

Personality traits: Information systems research focuses on examination of the IT artifact and the individual's response to same in diverse contexts. However, individuals are not a homogenous group and as a consequence, more recently the examination of personality traits in IS literature has gained considerable attention (Barnett *et al.*, 2015; XI Chen, Pan and Guo, 2016; Kim, 2018). However, whether personality traits influence self-disclosure within the context of DHPs remains a matter of speculation to date (Bansal, Zahedi and Gefen, 2010; Nguyen, Bin and Campbell, 2012; Badreddine, Blount and Quilter, 2022).

Culture and context: Finally, with regard to the context of this study, researchers agree that cultural differences have received too little attention in the study of online health. As such, the combination of Irish data and American data in this study contributes to research calls into health information concerns in both a European context and a cross cultural context (Bansal, Zahedi and Gefen, 2010; Anderson and Agarwal, 2011; Bélanger and Crossler, 2011; Dinesen et al., 2016; Lowry, Dinev and Willison, 2017)

2.7.1 Justification of Hypotheses

Based on the literature review and the corresponding gaps in knowledge that have been identified this chapter concludes was a presentation of the justifications for the hypotheses of this research study.

2.7.1.1 HIPC and Self-Disclosure

Information privacy concerns in an online context have been shown to affect outcomes as diverse as online shopping (Posey and Ellis, 2007), social media use (Zhong *et al.*, 2022) and mobile health technology adoption (Fox and Connolly, 2018). There is also evidence that these privacy concerns may also influence online self-disclosure. For example, Posey *et al.*, (2010) found that privacy concerns negatively influence self-disclosure in the context of online work platforms and that this is a direct relationship independent from other variables. Other researchers such as Bansal, Zahedi and Gefen, (2010) found HIPC to have a direct negative relationship with disclosure intentions for users of health websites, as well as an indirect influence through its effect on trust. Although this latter research employed only a 3 item measure of HIPC and involved a lab experiment, the findings confirm the restricting potential of these concerns on health information disclosure in an online context, an outcome that is not surprising as health data is distinctively more sensitive than many other data types. However, whether the influence of HIPC in a DHP context is direct (as indicated by the work of Posey et al, 2013) or whether its effect is expressed through its effect on trust beliefs (as indicated by the work of Taddei and Contena, 2013) is unclear and merits detailed attention. In order to determine that fact and based on extant literature, the following is proposed;

H1: In a DHP context, HIPC will reduce self-disclosure behaviour.

2.7.1.2 THP and Self-Disclosure

Disclosing information about health, with its associated sensitivities, requires trusting expectation of a positive outcome, including that the information will not be exploited or result in negative outcomes for the discloser. For that reason, researchers have long found trust to exert a significant role in generating online disclosures in online social community platforms, ecommerce sites and social networks (Posey *et al.*, 2010; Taddei and Contena, 2013; Shih, Lai and Cheng, 2017). It has also been found to help generate health information disclosure *intentions* on health websites (Bansal, Zahedi and Gefen, 2010). However, the literature increasingly acknowledges the difference between measuring intentions, as opposed to actual behaviour (Anderson and Agarwal, 2011; Fox and Connolly, 2018), and thus researchers have called for research which examines disclosure behaviour, as opposed to disclosure intention (Anderson and Agarwal, 2011; Dinesen *et al.*, 2016), as well as for greater clarity as to whether and how trust influences self-disclosure behaviours in online health contexts (Vega, Montague and

DeHart, 2010; Vega, Montague and Dehart, 2011; Fox and Connolly, 2018). Based on this discussion the following hypothesis is proposed;

H2: In a DHP context, THP will increase self-disclosure behaviour.

2.7.1.3 HIPC and THP

There is much research demonstrating that information privacy concerns influence trust in a multitude of online contexts including that of online service adoption (Harborth and Pape, 2020); online shopping (Connolly and Bannister, 2007) and even eGovernment adoption (Sipior *et al.*, 2013). However, when health information privacy concerns are examined in relation to trust, this has provided mixed findings to date. Some of this relates to the positioning of the relationship and varying contextual foci. For example, the work of Fox and Connolly, (2018) positioned trust as influencing HIPC in the context of mHealth adoption intentions, confirming that relationship. However, the work of Bansal, Zahedi and Gefen, (2010) found HIPC to have no significant relationship with trust in the context of health websites, although the fact that the measure of HIPC in that context was limited may have influenced the findings. Recent work by Wu *et al.*, (2022) would appear to provide a valuable guide in regard to the direction of the relationship. These researchers examined engagement in online health communities, and their findings show that health information privacy concerns reduce such engagement and its associated trusting behaviour. As other research (Connolly et al, 2022) has also shown engagement in online health communities to derive from trust beliefs and express in trusting behaviour, it is reasonable to consider that HIPC may reduce trusting beliefs in a DHP context. The current research will examine this relationship in the context of online disclosures of health information using a comprehensive HIPC measure based on the work of Hong and Thong, (2013). Based on this discussion the following hypothesis is proposed;

H3: In a DHP context, HIPC will reduce THP.

2.7.1.4 Privacy Risk Beliefs and HIPC

Much research has been undertaken to understand general privacy risk beliefs (Malhotra, Kim and Agarwal, 2004), however less is known about how such risk beliefs impact more specific health information privacy concerns. HIPC is understood as an individual's concerns regarding collection, use and dissemination of their personal data (Hong and Thong, 2013) and has attracted much attention in IS literature (D'Arcy, Hovav and Galletta, 2009; Bansal, Zahedi and Gefen, 2010; Anderson, Agarwal and Anderson, 2011; Hwang et al., 2012; Kordzadeh, Warren and Seifi, 2016; Hallam and Zanella, 2017; Lowry, Dinev and Willison, 2017). Recent research in the context of mHealth adoption (Fox and Connolly, 2018) has shown privacy risk beliefs and HIPC to have a positive relationship in the context of mHealth technology adoption. Although such an effect may also extend to DHP contexts, this cannot be assumed, as recent research by Chua, Ooi and Herbland, (2021) reveals that individuals can have different levels of concern for different data types. Therefore, research examining whether privacy risk beliefs accentuate HIPC in relation to self-disclosure across DHPs is merited, as is whether this relationship varies across cultures. Based on this discussion the following hypothesis is proposed;

H4: In a DHP context, privacy risk beliefs will increase HIPC.

2.7.1.5 Privacy Risk Beliefs and THP

Privacy risk beliefs have long been associated with reduced trust, be it in people, organisations or technology (Mayer, Davis and Schoorman, 1995; Lankton, Mcknight and Tripp, 2015). Previous research suggests that privacy risk beliefs can reduce trust in a context of health technology adoption. For example, Yi et al., (2013) showed perceived risk to have a modest negative relationship to trust in health websites, while the work of Fox and Connolly, (2018) found an inverse relationship between perceived risk beliefs and trust in eHealth adoption. In a disclosure context, the work of Bansel, Zahedi and Gefen (2010) has shown that privacy risk beliefs exert a negative influence on willingness to trust and intention to disclose on health websites. Whether this relationship extends more broadly to DHPs and whether it is culture independent is unclear and merits further attention. Based on this discussion the following hypothesis is proposed;

H5: In a DHP context, privacy risk beliefs will reduce THP.

2.7.1.6 Perceived Reciprocity

Reciprocity has long been associated with the establishment of a trusting environment (Jourard, 1971; Posey *et al.*, 2010; Sánchez-Franco and Roldán, 2015) and important theoretical frameworks such as social penetration theory view it as a critical to the development of a trusting relationship (Altman & Taylor 1973). In an online context, contemporary research also links it with development of trust, whether in relation to ecommerce (Posey and Ellis, 2007; Roethke *et al.*, 2020) or in a social media context (Alaqra and Wästlund, 2019; Khalil, Zia and Abdallah, 2019). Research also links reciprocity with trust and self-disclosure, in that when an environment is perceived to be low in risk, deeper revelations occur and as reciprocation of revelation is experienced the intimacy of these revelations also grows in amount and depth (Posey and Ellis, 2007; Posey *et al.*, 2010; Tamir and Mitchell, 2012). However, much of that research has now examined the relationship between reciprocity and trust (as a predictor of disclosure) explicitly, instead positioning both variables as independently influencing self-disclosure without considering their inter-relationship. This does not take into account pre-existing literature which clearly conceptualises a relationship between both reciprocity and trust. For that reason, empirical research examining whether reciprocity serves as a predictor of trust in a DHP health information disclosure context would benefit our understanding of how trust can be more effectively generated in such a context. Based on this discussion the following hypothesis is proposed;

H6: In a DHP context, perceived reciprocity will increase THP.

Research examining the relationship between reciprocity and health information privacy concerns is notably lacking. This may be because reciprocity tends to be viewed positively and is therefore considered in terms of its effect on positive outcomes such as trust generation. However, as trust beliefs exist in a context of risk (Mayer et al, 1995), it is surprising that the relationship between reciprocity and risk beliefs, such as HIPC have not received adequate attention. Whether this relationship exists in DHP context remains undetermined. It is therefore proposed that:

H7: In a DHP context, perceived reciprocity reduces HIPC.

2.7.1.7 Social Influence

Social influence has been described by Deutsch and Gerard, (1955) as the degree to which an individual's beliefs, attitudes and behaviours are influenced by those in their environment. While it has long been associated with the development of trusting environments in offline contexts (Fishbein and Ajzen, 1975; Cialdini, 2001), it has also been shown to have a role in online trust generation (Zhou and Li, 2014; Shih, Lai and Cheng, 2017; Adjekum, Blasimme and Vayena, 2018). For example, Shih, Lai and Cheng, (2017) have shown digital consumers in Taiwan to be subject to social influence by way of building dependency in online groups which in turn leads to trust formation. Although research (Posey *et al.*,2010) has found social influence and trust to exert a direct influence on online self-disclosure, the relationship between both variables was not examined. This is particularly surprising given the copious literature which supports a relationship between social influence and trust. For that reason, empirical research examining whether social influence serves as a predictor of trust in a DHP context would be particularly valuable.

While it is not surprising that social influence should positively influence online trust formation it is surprising to find that little to no research has examined the nature of the relationship between social influence and privacy concerns in an online disclosure context. For example, it is not known if social influence could alleviate health information privacy concerns via a positive group dynamic. Base on this discussion, it is proposed that:

H8: In a DHP context, social influence will increase THP.

Although there is evidence that both social influence and privacy concerns separately influence self-disclosure in an online community (Posey et al, 2010), the nature of the relationship between these constructs has not been examined in such a context. This is surprising given that social influence has been shown to influence privacy concerns in a multitude of contexts including Facebook advertising (Youn and Shin, 2019). Both explicit and implicit social norms have been shown to influence privacy behaviours on social networking sites (Spottswood and Hancock, 2017). This relationship also appears to remain consistent across cultures, with the work of Zhou and Li, (2014) on social networking continuance showing that social influence and privacy concerns are key inter-related factors that influence behavioural outcomes in China. Given these facts, the lack of empirical research to determine whether social influence influences HIPC in a DHP context is all the more remarkable. The following hypothesis is therefore proposed;

H9: In a DHP context, social influence will reduce HIPC.

2.7.1.8 Personality Traits and Self-Disclosure

IS researchers have started to recognize the influence of personality traits on outcomes (Barnett *et al.*, 2015; XI Chen, Pan and Guo, 2016; Kim, 2018). However, it remains an underexplored topic within the context of online health (Bansal, Zahedi and Gefen, 2010; Nguyen, Bin and Campbell, 2012; Badreddine, Blount and Quilter, 2022). This is despite IS research indicating that personality traits can have a direct influence on disclosure activity (Kim, 2018; D'Agata, Kwantes and Holden, 2021). Moreover, as SPT posits that relationships develop over time from shallow to intimate disclosures and that an individual's core personality will emerge as information exchanges become deeper (Altman and Taylor, 1973), it stands to reason that individuals high in certain personality traits will move from shallow to deep disclosures with more ease than others. For example, individuals high in trait neuroticism may find it more difficult to develop relationships and share personal information when compared with individuals high in trait openness, due to possible anxiety issues (Costa and McCrae, 1992; Costa, Terracciano and McCrae, 2001). Whether observations like this hold true in an online health context is unclear. This study therefore examines the role of personality traits in online self-disclosure of health information as it may impact the sharing of critical health information by patients and users.

Agreeableness refers to being helpful, cooperative, and sympathetic toward others and relates to compassionate and emotional affiliation with others (DeYoung, Quilty and Peterson, 2007). It is associated with respect and is present when relationships develop. Research into personality traits and online disclosure levels in non-health contexts have found individuals high in trait agreeableness to disclose personal information online (Hollenbaugh and Ferris, 2014), as did D'Agata, Kwantes and Holden, (2021) and Chan, (2021) who also found that individuals high in trait agreeableness more willing to share personal information online. In an online health context, previous research has found agreeableness to be positively associated with perceived health information sensitivity (Bansal, Zahedi and Gefen, 2010), while Badreddine, Blount and Quilter, (2022) found individuals high in trait agreeableness to exhibit higher disclosure levels when examining communication levels among cancer patients on online communities. However, as there exists only a small amount of research that examines its relationship with self-disclosure in the context of personal health information on DHPs further examining is required. Based on this discussion the following hypothesis is proposed;

> **H10: In a DHP context, an individual's agreeableness will increase their self-disclosure**

Conscientiousness refers to a desire to do a task well and is associated with caution and risk averse tendencies (McCrae and Costa, 1997; XI Chen, Pan and Guo, 2016). As such individuals high in trait conscientiousness may deem the sharing of sensitive health information as risky behaviour and reduce their disclosures. Research in online disclosures of non-health data found conscientiousness to be associated with suspicion, suggesting conscientiousness individuals to be more cautious when communicating online (D'Agata, Kwantes and Holden, 2021). In an online health context Bansal, Zahedi and Gefen, (2010) however found no signifcant relationship between conscientiousness and perceived health information sensitivity. Badreddine, Blount and Quilter, (2022) found individuals high in trait conscientiousness to exhibit lower disclosure levels when examining communication levels among cancer patients on online communities, but that these individuals did tend to lurk and passively partake in their online health community. This lack of clarity, particularly in a health context merits further investigation as to the role of conscientiousness in the context of personal health information on DHPs and as such further examining is required. Based on this discussion the following hypothesis is proposed;

> **H11: In a DHP context, an individual's conscientiousness will decrease their self-disclosure.**

Openness reflects strong intellectual curiosity and a preference for novelty and variety, it is a personality trait that describes how open a person is to new experiences and ideas (Costa and McCrae, 1992). Individuals who are open are often willing to try new things and explore different perspectives (Costa, Terracciano and McCrae, 2001). Individuals who are low in openness tend to be more traditional and conservative, preferring to stick to familiar routines and ideas (Costa and McCrae, 1992; Correa, Hinsley and de Zúñiga, 2010; Hollenbaugh and Ferris, 2014; Kim, 2018). Research into personality traits and online disclosure levels in non-health contexts have revealed openness to be associated with higher levels of self-disclosure (Hollenbaugh and Ferris, 2014), however D'Agata, Kwantes and Holden, (2021) did not find that individuals were necessarily open to forming new connections in online environments. This may be due individuals high in trait openness being more satisfied with offline connections. In an online health context Bansal, Zahedi and Gefen, (2010) found directional support for a negative relationship between openness and perceived health information sensitivity however this relationship was not significant. Badreddine, Blount and Quilter, (2022) found individuals high in trait openness to exhibit higher disclosure levels when examining communication levels among cancer patients on online communities. These mixed results, particularly in a health context merits further investigation as to the role of conscientiousness in the context of personal health information on DHPs and as such further examining is required. Based on this discussion the following hypothesis is proposed;

> **H12: In a DHP context, an individual's openness will increase their self-disclosure.**

Extroversion is reflected in a high degree of sociability, assertiveness, and talkativeness, it is a personality trait characterized by a focus on external activities and a preference for social interaction (Costa and McCrae, 1992). People who are extroverted tend to be outgoing, talkative, and energetic. They often enjoy being around other people and thrive in social situations (Costa, Terracciano and McCrae, 2001; Nadkarni and Hofmann, 2012). They tend to be more assertive and take initiative in conversations and activities. They also tend to be more open to new experiences and more likely to take risks (Costa and McCrae, 1992; Correa, Hinsley and de Zúñiga, 2010; Hollenbaugh and Ferris, 2014; Kim, 2018). Research into personality traits and online disclosure levels in non-health contexts have found extroversion to be associated with higher levels of self-disclosure (Hollenbaugh and Ferris, 2014), however as was the case with openness, D'Agata, Kwantes and Holden, (2021) did not find that individuals high in trait extroversion were necessarily open to forming new connections in online environments. Again, this may be due individuals high in trait openness being more satisfied with offline connections. In an online health context Bansal, Zahedi and Gefen, (2010) found no support for a negative relationship between extraversion and perceived health information sensitivity. Badreddine, Blount and Quilter, (2022) found individuals high in trait extroversion to exhibit higher disclosure levels when examining communication levels among cancer patients on online communities. These mixed results, particularly in a health context merits further investigation as to the role of extroversion in the context of personal health information on DHPs and as such further examining is required. Based on this discussion the following hypothesis is proposed;

H13: In a DHP context, an individual's extroversion will increase their self-disclosure.

Neuroticism refers to the degree of emotional stability, impulse control, and anxiety, it is a personality trait that is characterized by a tendency to experience negative emotions such as anxiety, fear, anger, and depression (Costa and McCrae, 1992; Costa, Terracciano and McCrae, 2001; Junglas and Johnson, 2008). Individuals who are high in trait neuroticism tend to be more sensitive to stress and more likely to experience negative emotions. They can be irrational as this trait is associated with being easily influenced, often through fear (Costa and McCrae, 1992; Correa, Hinsley and de Zúñiga, 2010; Hollenbaugh and Ferris, 2014; Kim, 2018). As such individuals who are more anxious and have higher levels of neuroticism may be more likely to disclose more health information than those who are less anxious (Chan, 2021). Research into personality traits and online disclosure levels in non-health contexts have found individuals low in trait neuroticism to disclose more than those high in trait neuroticism (Hollenbaugh and Ferris, 2014), however D'Agata, Kwantes and Holden, (2021) found that individuals high in trait neuroticism were more open to sharing information online. This could be due to individuals with anxiety finding it easier to form bonds online than in an offline context. In an online health context Bansal, Zahedi and Gefen, (2010) found support for a negative relationship between neuroticism and perceived health information sensitivity. Badreddine, Blount and Quilter, (2022) found mixed results with regard to disclosure levels and neuroticism when examining communication levels among cancer patients on online communities. Interestingly Nikbin, Iranmanesh and Foroughi, (2020) found that trait neuroticism was associated with Facebook addiction, indicating that individuals can form dependencies with digital platforms. These mixed results, particularly in a health context merits further investigation as to the role of neuroticism in the context of personal health information on DHPs and as such further examining is required. On this evidence it is posited that neuroticism increases self-disclosure of personal health information on DHPs due to possible health related anxiety coupled with a possible need to communicate (Perry *et al.*, 2018). Based on this discussion the following hypothesis is proposed;

> **H14: In a DHP context, an individual's neuroticism will increase their self-disclosure.**

3 Chapter Three: Research Methodology

3.1 Introduction

The following chapter sets out the research methodology, the underlying research philosophy and the ensuing research design that was used for this study. A mixed methods research approach is presented as is the sampling strategies. Finally, the process of data collection for quantitative surveys and qualitative interviews is explained. The chapter structure is illustrated below in Figure 3.1.

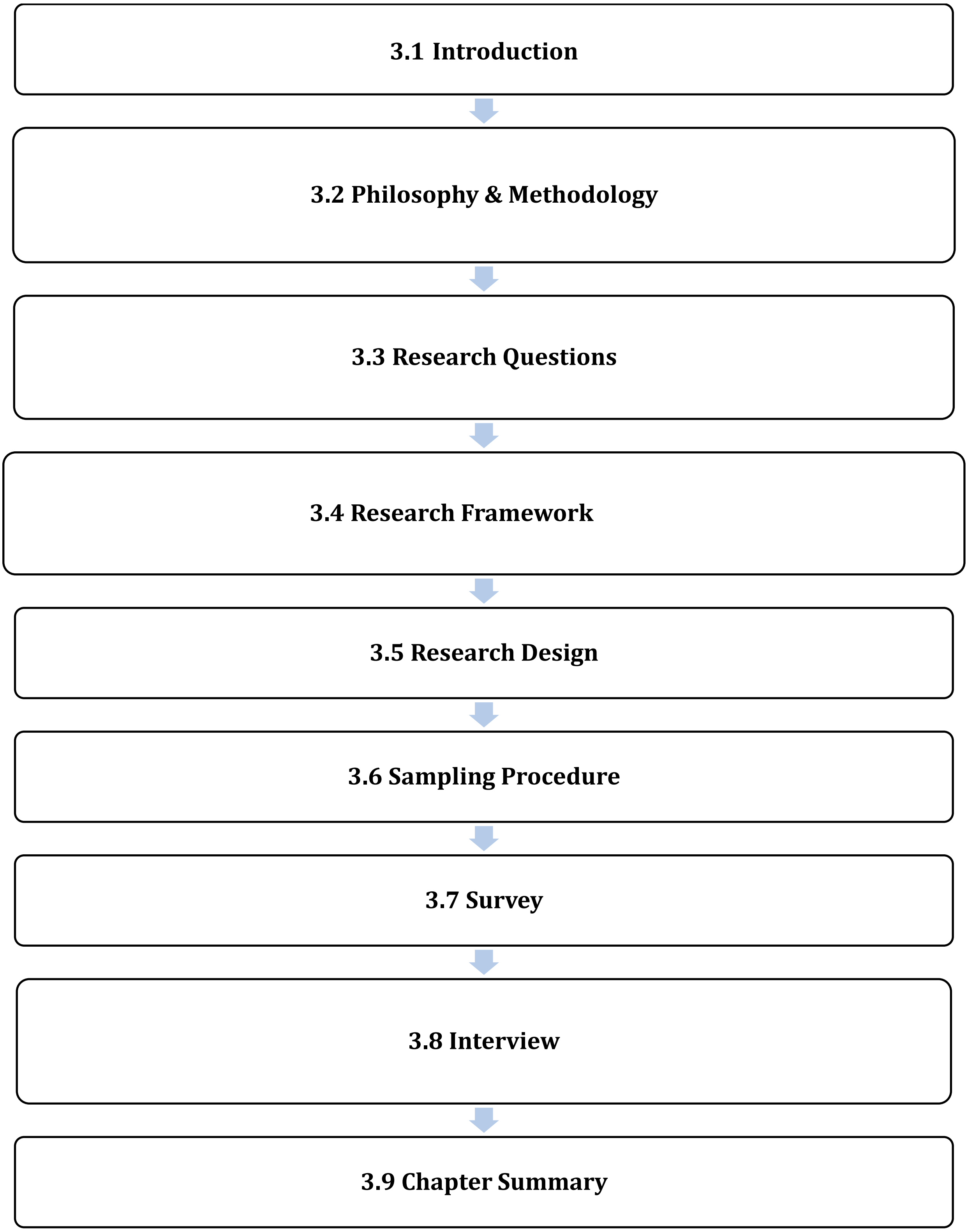


Figure 3.1 Chapter Structure

3.2 Philosophy & Methodology

It is impossible to be perfectly objective and remove the researcher's intrinsic worldviews from the research. As such a researcher must uncover their worldview and philosophical underpinnings so as to understand the implicit paradigms they will bring to a study (Creswell and Plano Clark, 2011). Traditionally a researcher will choose between one of three research methodologies in order to satisfy their philosophical leanings. For a considerable amount of time research in the area of information systems has been heavily influenced by the quantitative research methodology, indeed there was a time when the qualitative research methodology was all but dismissed within IS research (Sarker *et al.*, 2018), however this attitude has begun to change in recent years. This change has come with a growing appreciation for a mixed methods approach in information systems research (Venkatesh, Brown and Bala, 2013; Venkatesh, Brown and Sullivan, 2016). This change also brings with it a need to consider the underlying philosophical positions available to researchers. The following sections will present the predominant research philosophies used in IS research. Afterwards the chosen paradigm will be presented.

3.2.1 Finding a Philosophical Position

When considering a philosophical stance, one must pay heed to all of the building blocks that can be used to produce a researcher's worldview. Kuhn, (1962) described a philosophical paradigm as a map of a domain's ontology, epistemology and methodology. This section will now discuss the options available when building such a map.

3.2.1.1 Ontology

Ontology is defined as the philosophical assumptions about the nature of reality (Creswell and Plano Clark, 2011). Bell, Bryman and Harley, (2018) extend this definition to include how reality is conceptualised. To this end two predominant ontological positions exist; objectivism and constructivism. Both of these are presented in the table 3.1 below:

Ontology	***Definition***
Objectivism	Social phenomena and their meanings exist outside of human behaviour and control
Constructivism	Researchers use a specific definition of social reality depending upon the phenomenon researched, rather than an overarching definitive version. Social phenomena exist under the control and influence of human behaviour.

Table 3.1 Ontology **Source: Bell, Bryman and Harley, (2018)**

The objectivist position is similar to that of the position taken by a physical scientist (Johnson and Onwuegbuzie, 2004). An objectivist position holds that reality exists independently of our beliefs or understanding (Bell, Bryman and Harley, 2018). As such objectivist studies should be time and context free. As a result, scientific outcomes are presumed valid and reliable, and the reporting language should be neutral, formal and focused on the establishment of laws. Objectivism has a long association with quantitative research.

Constructivism, on the other hand is generally associated with qualitative research. This position is considered pluralist. It holds that multiple constructed realities can exist and that time and context free studies are not possible (Johnson and Onwuegbuzie, 2004; Scott and Briggs, 2009). Under constructivism an informal and rich reporting language is favoured, the use of quotes is encouraged over numeric data, and logic can flow from the specific to the general. This approach reflects the constructivist position that social phenomena and their meanings are produced through social interaction and are in a constant state of revision (Seale, 2018).

3.2.1.2 Epistemology

Epistemology is defined in the Oxford Dictionary as “the theory of knowledge, especially with regard to its methods, validity, and scope, and the distinction between justified belief and opinion” (Oxford, 2022). Due to its broad definition it is often synonymous with methodology. Epistemological positions have been widely covered by researchers Creswell and Plano Clark, (2011) and Bell, Bryman and Harley, (2018) who opt to present them under a number of definitions all of which are outlined in the table 3.2 below:

Epistemology	***Definition***
Positivism	Imitation of the natural sciences. Requires empiricism, uses deductive theory, observations are objective, and conceptualisations of reality directly reflect reality as it is. Reality still exists regardless of human existence, influence, or interpretation.
Realism	Identifies links between the ‘real’ world and the research conducted. Internal realism suggests it is only possible to gather indirect evidence and support for studied phenomena (physical & social). Naïve realism ignores the un-testable elements of social research but acknowledges they may exist. Critical realism conceptualises reality as a way of understanding what is happening in the social world, and acknowledges and embraces the un-testable elements between the research conducted and the real world.
Relativism	Similar to realism but acknowledges that people/social groups are the subject matter, not physical/natural science elements. Different observers have different points of view thus affecting the derived knowledge/value/truth

Postmodernism	Aims to redress the excesses of modernism. Typically concerned with an eclectic approach, arguing scientific progress is discontinuous and contestable. It is against systematic control and supports flexibility.
Pragmatism	There are no pre-determined theoretical frameworks that determine knowledge and understanding, within the social world. Structure is derived from an individual's experience. Decisions & reality are assumed on a case-by-case basis.
Interpretivism	Identifies the social sciences as fundamentally different to the natural sciences. Interpretivism embraces an empathetic approach to human behaviour, interpreting observations of research, acknowledging that the core elements of such are directly un-testable.

Table 3.2 Epistemology
Source: Creswell and Plano Clark, (2011) and Bell, Bryman and Harley, (2018)

A number of competing and differing philosophical, ontological and epistemological views exist within the research community. Further to this the three research methodologies (quantitative, qualitative and mixed methods) bring with them their own traditions and paradigms. For this reason, one must consider closely their own assumptions on the nature of reality, their worldview and the research context. Ultimately a researcher's decision during this process will have an influence on their data collection, data analysis and data interpretation.

3.2.2 Pragmatism as a Research Philosophy for Mixed Methods Research

Quantitative and qualitative research methods bring with them their own underlying philosophies and a mixed method research approach is no different. Indeed, it had historically been argued that it was not possible to merge two competing philosophical paradigms under one research method, though this debate has been much reduced (Teddlie and Tashakkori, 2009; Creswell and Plano Clark, 2011). When considering the underlying philosophical paradigm of a mixed methods research approach it is generally now agreed that four primary paradigms exist; post-positivism, constructivism, transformative and pragmatism, (Creswell and Plano Clark, 2011). Of the four available philosophical paradigms, pragmatism offers a single paradigm approach. As such it overcomes the many hurdles associated with trying to employ two competing outlooks (Morgan, 2007). At its core pragmatism puts forward that in any one moment both singular and multiple realities or truths can exist (Morgan, 2007; Scott and Briggs, 2009; Teddlie and Tashakkori, 2009; Tashakkori and Teddlie, 2010; Creswell and Plano Clark, 2011). This would be in stark contrast to a positivist outlook, as an example. The pragmatic paradigm is flexible and offers practical insights to observed phenomena while employing deductive to inductive reasoning. Pragmatism is favoured within the social and health sciences (Morgan, 2007; Scott and Briggs, 2009) due to this flexibility and its practical outputs and as such is the chosen research philosophy underpinning this study. This flexibility and other key components of the pragmatic paradigm are outlined and compared with other available paradigms in the table 3.3 below:

	Post positivism	***Constructivism***	***Pragmatism***
Ontology (belief regarding nature of reality)	Singular reality: Hypotheses are rejected or accepted	Multiple realities: meaning is generated via human interactions and interpretations	Singular and multiple realities: test hypotheses and present multiple perspectives
Epistemology (how we know what we know)	Distance and impartiality: data is objectively collected	Closeness: researchers visit sites to collect data	Practicality: data is collected by 'what works' to address research questions
Axiology (how value is derived)	Unbiased: checks are utilised to eliminate bias	Biased: researchers discuss bias and interpretations	Multiple stances: biased and unbiased perspectives included
Methodology (process of research)	Deductive: hypothesis is tested	Inductive: begin with participants' views and build up to theory	Combination: quantitative and qualitative data are collected and mixed
Rhetoric (how to write about the research)	Formal: use agreed upon variable definitions	Informal: researchers write in literary style	Formal or informal: researchers can employ both writing styles of writing

Table 3.3 Research paradigms **Source: Creswell and Plano Clark, (2011)**

The specific steps taken to employ this paradigm along with a mixed methods research approach have been heavily influenced by the works of Creswell and Plano Clark (2011), Venkatesh, Brown and Bala (2013) and Venkatesh, Brown and Sullivan, (2016). The following sections will detail the quantitative, qualitative and mixed methods approach. Afterwards the steps taken to employ a mixed methods approach will be discussed.

3.2.3 Quantitative vs. Qualitative Methodologies

Quantitative methodologies have been the chosen paradigm in IS research until recently and are strongly attached to a positivist outlook (Sarker, Xiao and Beaulieu, 2013; Sarker *et al.*, 2018). Though there are many differences of opinion on how best to define the positivist outlook, it is generally agreed that positivism has a deep scientific root and holds that all phenomena can be singularly defined and measured (Eidlin, 2014). It is not surprising, therefore, that quantitative methodologies have been so heavily associated with the positivist paradigm. Quantitative methods do allow for clean data analysis and the easy repetition of measurement of phenomena (Bell, Bryman and Harley, 2018). That said, the positivist outlook is considered out of date within the social sciences (Clark, 1998). There are a number of reasons for this chief among them a fixation on numbers and the exclusion of the human experience (Bell, Bryman and Harley, 2018). As a result, it is acknowledged that a quantitative approach at its most basic level offers a limited, static insight into a phenomenon. More recently the post-positivist paradigm has emerged wherein which the philosophical outlook of the researcher has been acknowledged as having an influence on the research being undertaken and that theory cannot prove causation (Tashakkori and Teddlie, 2010).

Recent writings on the topic of qualitative research within IS (Sarker, Xiao and Beaulieu, 2013; Sarker *et al.*, 2018) have shown a slow but steady trend in more papers being published in the area that utilise a qualitative methodology. This is significant because a qualitative approach brings with it its own philosophical paradigm to which it is predominantly associated with; constructivism. This paradigm holds that a researcher will attempt to interpret data from an observed phenomenon and construct meaning from it (Tashakkori and Teddlie, 2010). The growing number of qualitative studies in the area of IS brings with it the opportunity to develop deeper understanding of the personal experiences of participants (Creswell and Plano Clark, 2011). This does however bring with it a number of limitations associated with the qualitative methodology; replication is difficult; subjectivity is prevalent; researcher bias is inherent; it is difficult to generalise findings (Creswell and Plano Clark, 2011; Bell, Bryman and Harley, 2018).

3.2.4 Mixed Methods Research

The last 30 years has seen the emergence of a third methodological movement, mixed methods research, which attempts to bring aspects of qualitative and quantitative methodologies together (Tashakkori and Teddlie, 2010; Venkatesh, Brown and Sullivan, 2016). This movement has brought with it much debate about how best one can combine competing philosophical paradigms under one methodology but there is general agreement that a mixed method approach brings with it a great opportunity to develop more complete and holistic understandings of phenomena (Venkatesh, Brown and Bala, 2013; Bell, Bryman and Harley, 2018). By combining the best of what both previous methodologies have to offer, a mixed method research approach allows for stronger, more accurate inferences of data, presentation of divergent, complimentary or convergent findings and the elimination of weaknesses associated with quantitative and qualitative research methodologies when used alone. It is however noted that a mixed method research approach is time consuming and can be more difficult to complete, (Tashakkori and Teddlie, 2010; Creswell and Plano Clark, 2011).

The present study has elected to use a mixed methods research approach for a number of reasons. First there is a dearth of studies in the IS research community that uses this approach and as such many have worked to bridge this gap (Venkatesh, Brown and Bala, 2013). Second, this study aims to develop a complete, accurate and holistic insight into the phenomenon of user self-disclosure on digital health platforms. Third, the research questions that form this study allow for both a quantitative examination of contemporary and established constructs while also benefitting from a deeper examination of users' personal experiences by way of qualitative interviews. This combination allows for the construction of multiple realities and practical insights, as supported by a mixed methods research approach that is underpinned by a pragmatic worldview (Creswell and Plano Clark, 2011; Venkatesh, Brown and Sullivan, 2016; Bell, Bryman and Harley, 2018).

3.3 Research Questions and Hypotheses

Set as a two country comparison (Ireland and USA), this study aims to explore and compare the factors that can influence self-disclosure on digital health platforms. To that end, two primary antecedents, trust and health information privacy concerns (HIPC) are examined in detail, in terms of their relationship as potential motivators or diminishes of self-disclosure. The influential role of social influence and reciprocity in relation to both of these constructs is also examined. Recognising that individuals can vary considerably in terms of their disclosure response, the research also includes an examination of the role of personality traits as a potential factor influencing self-disclosure of personal health information online.

The main research question is therefore:

1. What factors influence self-disclosure, (including amount and depth) on digital health platforms?

The subsidiary research questions are:

1a. What is the relationship between trust and self-disclosure in this context?

1b. What is the relationship between HIPC and self-disclosure in this context?

1.c. What is the relationship between privacy risk beliefs and HIPC in this context?

1.d. What is the relationship between HIPC and trust in this context?

1.e Does Social Influence and Reciprocity influence the formation of trust and HIPC in this context?

1.f Do personality trait variables influence self-disclosure in this context?

Summary of hypotheses based on literature review:

H1: In a DHP context, HIPC will reduce self-disclosure behaviour.

H2: In a DHP context, THP will increase self-disclosure behaviour.

H3: In a DHP context, HIPC will reduce THP.

H4: In a DHP context, privacy risk beliefs will increase HIPC.

H5: In a DHP context, privacy risk beliefs will reduce THP.

H6: In a DHP context, perceived reciprocity will increase THP.

H7: In a DHP context, perceived reciprocity reduces HIPC.

H8: In a DHP context, social influence will increase THP.

H9: In a DHP context, social influence will reduce HIPC.

H10: In a DHP context, an individual’s agreeableness will increase their self-disclosure

H11: In a DHP context, an individual's conscientiousness will decrease their self-disclosure.

H12: In a DHP context, an individual's openness will increase their self-disclosure.

H13: In a DHP context, an individual's extroversion will increase their self-disclosure.

H14: In a DHP context, an individual's neuroticism will increase their self-disclosure.

3.4 Research Framework

The underlying literature guiding the research framework has been discussed in the literature review chapter. The research framework for this study was constructed by consulting the self-disclosure, trust, risk and information privacy concerns literatures, as well as literature relating to the influence of personality trait variables on behavioural outcomes. In addition, literatures relating to theoretical considerations were also consulted, as advised by Burkholder *et al.*, (2019). A model proposed by Posey *et al.*, (2010), which examined online self-disclosures of office workers on online workplace communities was identified as containing important variables of interest and as being an important structural model for guiding the present research. It contained measures of particular interest which were expressed in a way relevant to the focus of the current study. These included the measures of privacy risk beliefs, self-disclosure, social influence and perceived reciprocity. However, other variables from the Posey *et al.*, (2010) model were not deemed to be relevant to the context of the present study and were therefore removed. For example, anonymity is not included in the current study as the digital health platforms examined in this study generally require a level of personal identification, as is the case with the many contemporary of health platforms (Paglialonga, Lugo and Santoro, 2018). Similarly, Posey *et al.*, (2010) had employed a simple measure of trust in online work platforms, adapted from Jarvenpaa and Leidner's, (1999) online teams trust measure. However, this was a very general measure of trust focusing on trust in online work communities. As a digital health platform is unique, and the consequences of disclosure are significant to the individual, a more comprehensive measure of trust in health platforms was adopted via a number of trust in online health studies such as Sillence, Briggs, P. Harris, *et al.*, (2007) and Harris, Sillence and Briggs, (2011) which both examined factors that influence trust in health websites and revealed design and information quality to have significant roles in trust development. While Li *et al.*, (2014) examined the role of trust in health technology vendors in trust formation of online health resources. The outcome was a measure that includes trust in design, trust in the health technology vendors and trust in information quality, each of which have been employed successfully in multiple trust in online health studies (Sillence, Briggs, P. R. Harris, *et al.*, 2007; Song and Zahedi, 2007; Sillence *et al.*, 2011; Li *et al.*, 2014; Fox and Connolly, 2018). It was therefore deemed a more effective and granular measure of trust and one that is likely to provide greater insight into the effect of the trust construct and its relationships.

Privacy risk beliefs are important motivators of behavioural response (Faries, 2016). However, the literature has shown a distinction between privacy risk beliefs that relate to more general concerns regarding online information privacy and those specific to health information (Fox and Connolly, 2018). Therefore, as is the case with Posey et al. (2010), this study recognises and seeks to capture the general privacy risk beliefs which relate to the online environment, but also includes a separate measure which specifically captures the health information privacy concerns. This enables a more precise examination and determination of the nature of privacy concerns, how they relate to trust beliefs and their influence on self-disclosure.

Finally, personality traits were included in the model. Much research on self-disclosure in an online health information context ignores the potential distinctions between individuals and their personality traits, this is despite previous IS research revealing that personality traits are deemed as having a considerable role to play in online behaviour in other contexts (Correa, Hinsley and de Zúñiga, 2010; Nadkarni and Hofmann, 2012; Barnett *et al.*, 2015), while a small but growing body of health information research has included personality trait examination (Bansal, Zahedi and Gefen, 2010; Badreddine, Blount and Quilter, 2022; Zhu, Jiang and Zhou, 2022) the role of personality traits in an online health disclosure context has not been comprehensively explored. In order to measure personality traits in this present research study a concise quantitative measure known as the Ten Item Personality Inventory (TIPI) (Gosling, Rentfrow and Swann, 2003), was used as it allows for a personality trait assessment to be conducted within a larger study.

In summary, an enhanced model has been constructed for the present study and context, this model was created by drawing more comprehensively from IS literature in order to produce a framework that reflects the sensitive nature of user self-disclosures on DHPs and the potential for consequential outcomes. This is achieved by incorporating variables which were selected due to their effective employment in previous online health information studies that examined issues related to information privacy concerns, trust and personality traits; HIPC (Fox and Connolly, 2018); THP (Sillence *et al.*, 2007, 2011; Li *et al.*, 2014); and personality traits (Gosling, Rentfrow and Swann, 2003; Bansal, Zahedi and Gefen, 2010).

Finally, based on IS literature the assumed relationship between variables was re-evaluated. Previous research such as Posey et al., (2010), had positioned all independent variables as having a direct relationship with the dependent variable, self-disclosure. However, the literature has provided repeated confirmation of the need to treat the relationship between variables with greater scrutiny when in the context self-disclosure of sensitive health information in an online context (Bansal, Zahedi and Gefen, 2010; Nguyen, Bin and Campbell, 2012; Hallam and Zanella, 2017; Yuchao, Ying and Liao, 2021). For this reason, these relationships have been reconstituted to produce a 2nd order construct model which posits an enhanced influential role for THP and also HIPC. This decision was also guided by SET and SPT which both posit a greater level of influence for trust and privacy when disclosing sensitive information. Added to this, personality traits are posited to play an influencing role on one's likelihood to self-disclose.

The outcome of this reconsideration, based on the literature, is a novel framework that provides a far more granular elucidation, not only of the role of HIPC and Trust on self-disclosure response, but also on the factors which may influence formation of those key constructs in the context of this study. It employs tested variables that have been used throughout IS literature. It recognises that the influence of these variables may shape the amount and depth of self-disclosure and that personality variables may also exert an effect. Moreover, the research model aligns with and draws on the guiding theoretical frameworks of SET, SPT and to a lesser extent CPM (Thibaut and Kelley, 1959; Altman and Taylor, 1973; Petronio, 2002). The research model or this study is illustrated below in figure 3.2

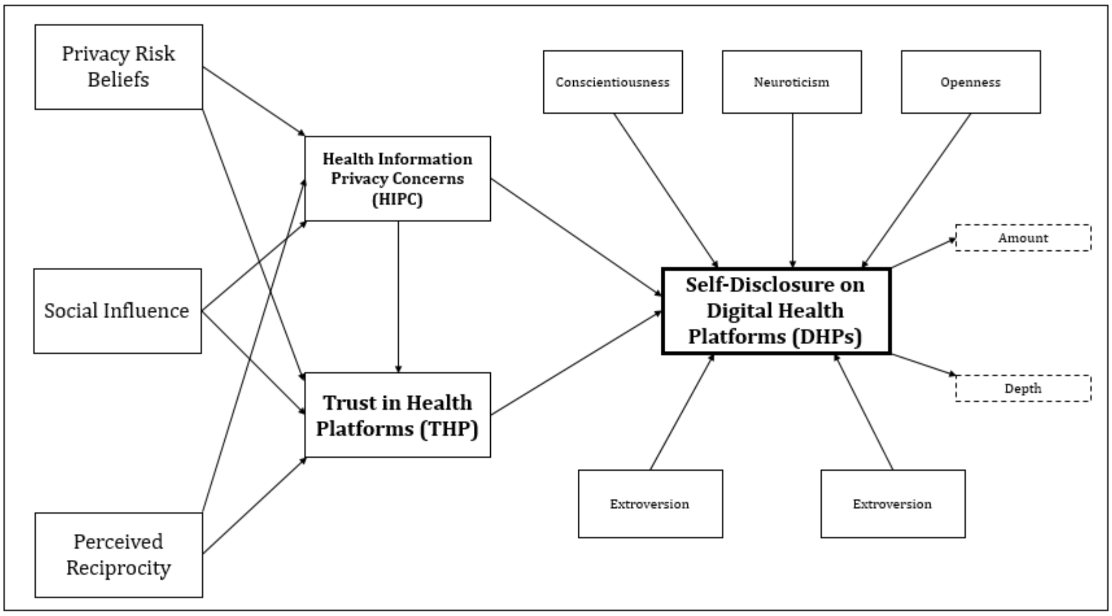


Figure 3.2 Research Model

3.4.1 Context Selection

This study is about users and their personal health information on digital platforms. Wearable DHPs that use sensors, such as Fitbits, are estimated to reach over 700 million individuals users by 2024 (Laricchia, 2022). These enable tracking of steps, movement, heart rate, ECG data, menstrual cycle, mood and sleep patterns (Al-Alusi *et al.*, 2019). Similarly, online health communities such as WebMD reach as much as 75 million unique users per month (WebMD, 2018). By the year 2025, the global value of DHPs is estimated to be €232 billion (Alharbi, 2021), with 3.7 billion mobile health application downloads occurring by 2017 alone (Stewart, 2019). In Ireland the Covid-19 tracker app was downloaded over one million times in the first 48 hours after its release (Health Service Executive, 2020). As more citizens and devices connect to digital health platforms more personal health information becomes susceptible to security issues and available to private entities (Lowry, Dinev and Willison, 2017). As global citizens continue to adopt digital health solutions this study looks at the factors that influence users to disclose personal health information on these platforms.

Currently Ireland ranks 6th last on health services expenditure per capita in the European Union, spending €23 million in 2019 (Eurostat, 2019). Yet the Irish government is in the middle of a 10-year plan to create a digitised health care system, SláinteCare, which would see every citizen issued unique health identifiers, development of electronic health records and a digital first approach across the health care system, (Department of Health, 2017).

The United States on the other hand presents a different health service story. Based on a more private health care model and far greater expenditure ($41.1 trillion in 2020), the citizens of the United States have had longer exposure to digital health systems and platforms, (U.S. Centers for Medicare & Medicaid Services, 2020).

With the above considered as a valuable contrast from which to gather insights it is also noted that the majority of IS research relating to health platforms is U.S. centric and research calls have been made to bridge this gap from a European perspective (Bélanger and Crossler, 2011). As a result, it is believed that this contextual study garners valuable insight from two contrasting geolocations while responding to calls for research in a European context and a security concern context.

The context of this study is one of asynchronous digital health platform disclosures by users who speak English and are residing in Ireland and the United States. These two cohorts represent two datasets with DHP experience but at different degrees of national exposure to digital health infrastructure.

Asynchronous disclosure refers to the act of sharing personal health information or experiences at a time that is convenient for the user, without the necessity for an immediate or real-time response (Quer *et al.*, 2021). This type of disclosure is facilitated by the nature of digital platforms, which allow users to post, comment, or share information whenever they choose.

Asynchronous disclosure contrasts with synchronous disclosure, which occurs in real-time interactions, such as a live chat or a face-to-face consultation with a healthcare provider.

The asynchronous nature of disclosure on digital health platforms can have several implications:

1. User Control: Users have more control over when and how they share their information, allowing them to carefully consider what they want to disclose, how they want to phrase it, and when they feel most comfortable sharing.

2. Privacy: Asynchronous disclosure can provide users with a sense of privacy and control over their information, as they can choose to share or withhold information based on their comfort level and perceived safety.
3. Accessibility: Asynchronous communication allows for more flexibility, making it easier for users who may have restrictions on their time or availability to still participate and disclose information on their own schedule.

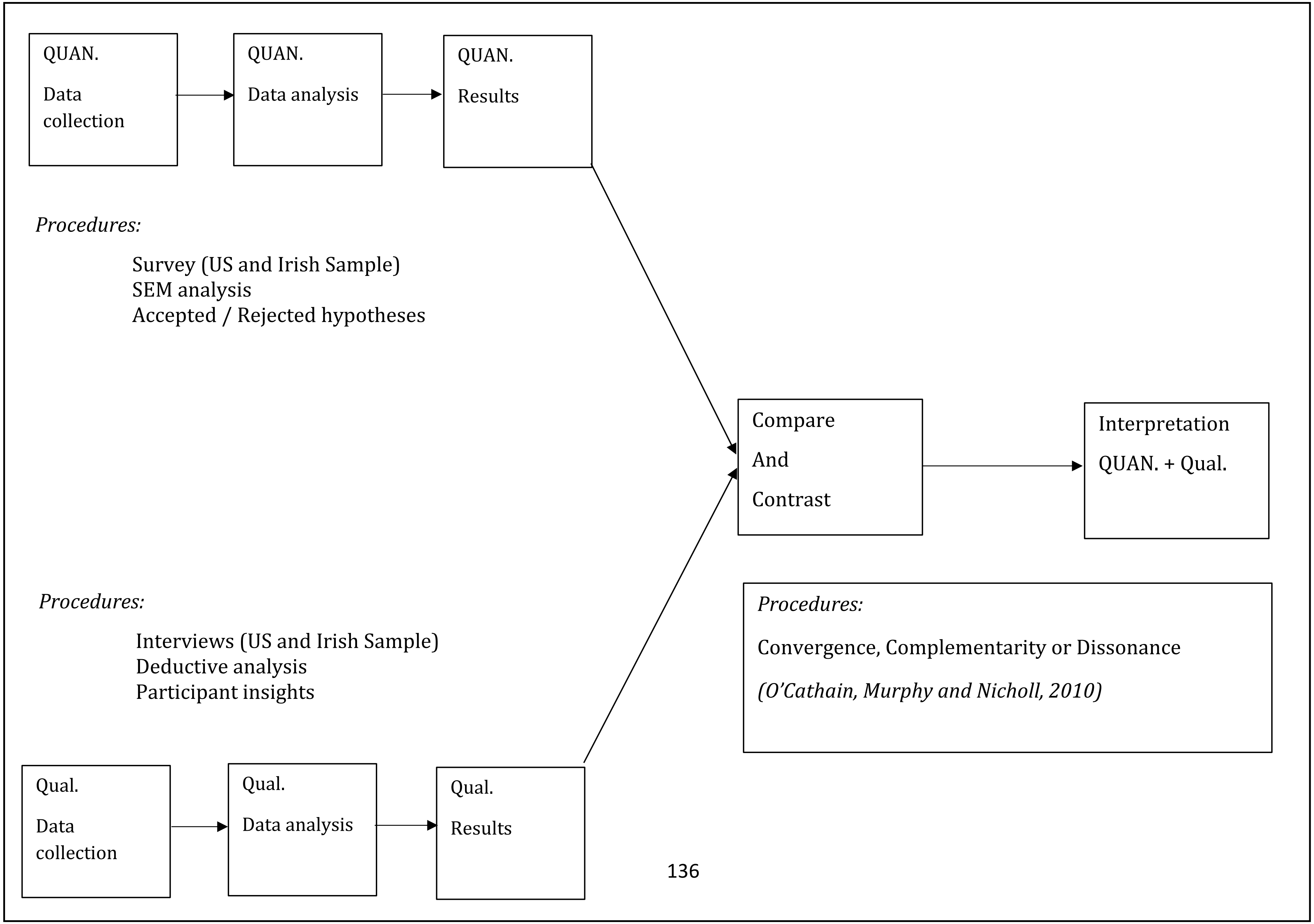
3.5 Research Design

A number of researchers have highlighted that there are various options available when considering a research design for a mixed methods research approach, (O'Cathain, Murphy and Nicholl, 2008; Creswell and Plano Clark, 2011; Venkatesh, Brown and Sullivan, 2016). Moreover, much of this same research has revealed that there is a need within the IS community to pay greater respect to the research design process, that researchers should clearly document the decision making process and justifications during this process. In an effort to comply with these recommendations this study will adopt reporting techniques put forward by Cathain, Murphy and Nicholl, (2008) and Venkatesh, Brown and Sullivan, (2016).

The research framework employed in this study was been constructed following review of a pre-existing framework (Posey *et al.*, 2010), radically altering it and enhancing it with a number of contemporary variables generated from literature. Following this a comprehensive quantitative survey instrument was developed and tested by a researcher peer group. Finally, an in-depth qualitative interview based on the quantitative survey was used to develop deeper understandings of the phenomenon that was being studied.

In accordance with Venkatesh, Brown and Sullivan, (2016), a strategy on how to undertake the research was devised. A two-stage sequential process that involves two separate stages of data collection was chosen, known as a convergence model. This convergence model (Creswell and Plano Clark, 2011) is a traditional mixed method approach that uses a triangulation design. In this model data is collected on the same phenomenon, first by a quantitative instrument and then a qualitative instrument. Afterwards data is compared in an effort to confirm or corroborate quantitative findings. The stages of the study are illustrated below in Figure 3.3

Figure 3.3 Convergence model



3.6 Sampling Procedure

A plethora of sampling procedures exist for mixed methods research. Many of these have been adopted from previous practices associated with quantitative and qualitative research and are detailed extensively by Venkatesh, Brown and Bala (2013) and Venkatesh, Brown and Sullivan (2016). Perhaps the most rigorous among these is an exploratory sampling procedure. With this approach, the researcher first collects qualitative data for the purpose of testing proposed relationships. Afterwards quantitative data is used to confirm the relationships. This is a time-consuming process, most appropriate when proposed relationships have not been studied before. As this study uses previously identified relationships (Posey *et al.*, 2010; Fox and Connolly, 2018; Fox and James, 2020) and was under time constraints, this approach was considered unsuitable for this context.

Venkatesh, Brown and Sullivan, (2016), have also presented four sampling strategies for mixed methods research that have been formulated on the back of previous work by Collins, Onwuegbuzie and Jiao, (2007) and Teddlie and Yu, (2007) are suitable in the present context. The four strategies are basic, sequential, concurrent, and multiple sampling designs. The table 3.4 below provides a brief outline of each:

Sampling designs	***Description***
Basic mixed- methods sampling strategies	The basic mixed-methods sampling strategies include purposive sampling and probability sampling. Purposive sampling refers to “selecting units (e.g., individuals, groups of individuals, institutions) based on specific purposes associated with answering a research study’s questions”. Probability sampling involves “selecting a relatively large number of units from a population, or from specific subgroups (strata) of a population, in a random manner where the probability of

	inclusion for every member of the population is determinable" (Teddlie and Yu, 2007, p77).
Sequential mixed- methods sampling	Sequential mixed-methods sampling involves selecting "units of analysis for an MM study through the sequential use of probability and purposive sampling strategies (QUAN-QUAL), or vice versa (QUAL-QUAN)" (Teddlie & Yu, 2007, p. 89)
Concurrent mixed- methods sampling	Concurrent mixed-methods sampling involves selecting "units of analysis for a mixed methods study through the simultaneous use of both probability and purposive sampling" (Teddlie & Yu, 2007, p. 89).
Sampling using multiple mixed-methods sampling strategies	These sampling techniques generally involve using multiple sampling strategies (e.g., using both sequential mixed-methods and concurrent mixed-methods sampling).

Table 3.4 Sampling Designs **Source: Venkatesh, Brown and Sullivan, (2016)**

This study elected to use the basic mixed methods sampling strategy as formulated by Teddlie and Yu, (2007). This strategy caters for probability sampling, stratified purposive sampling and purposive random sampling. As the aim of this study is to capture insights from citizens who actively participate in health information sharing on digital health platforms, and also in two separate countries, a purposive sampling design was used. Purposive sampling designs are best used when the researcher has prior knowledge about the purpose of their studies and when a population is clearly defined (Collins, Onwuegbuzie and Jiao, 2007).

Purposive sampling is a non-probability sampling method that is characterized by the use of judgment and a deliberate attempt to set criteria and select particular units of the population that would best serve the research objectives. As already stated, in this study, the purposive sampling process involved identifying and selecting individuals who were active participants on DHPs, residing in Ireland or the United States, older than 18 and speak English.

The basic mixed methods purposive sampling process employed included the following steps:

1. **Define the population**: The first step in the sampling process was defining the population. In this case, individuals who use digital health platforms, reside in Ireland or the United States, older than 18 and speak English.
2. **Set criteria**: Based on research objectives, specific criteria for participants included that they used a digital health platform for a length of time and disclosed health information.
3. **Identify potential participants**: With population and criteria set, I set out to identify potential participants. This included recruiting through University networks, email lists and other platforms.
4. **Select participants**: All effort was made to obtain participants from diverse backgrounds. On completion of surveys participants were then sought for follow up research interviews.
5. **Collect data**: After all surveys and interviews were complete both quantitative and qualitative datasets were prepared for analysis.

The purposive sampling process was justified in this study as it allowed focus on specific characteristics of a population that are of interest, which can best help answer the research questions (Venkatesh, Brown and Sullivan, 2016). In this case, the study was interested in self-disclosure on digital health platforms, so it was necessary to sample individuals who can provide in-depth and varied insights into this phenomenon based on their experience with DHPs.

The target population was to represent a cohort of English speakers who were active within their community (employed, in education or retired) and who had previous experience sharing health information online. Previous research has shown prior experience with online platforms to have a varying influence on user behaviour (Dinev, 2007). Some studies show exposure to online platforms to reduce one's willingness to continue use them, where other studies show the opposite effect (Smith, Dinev and Xu, 2011). For this reason, participants with a varied degree of experience with online platforms were recruited. It is noted that the sampling procedure for this study has limitations. Previous studies in the area have focused on more specific categories within samples however due to time and resource constraints a basic mixed methods sampling procedure was deemed sufficient.

Furthermore, participants were sought from Ireland and the United States for several other reasons:

a) Culture: While both countries are similar according to Hofstede's Dimensions (Hofstede, 2022), previous research has shown that national culture and regional culture can vary considerably and impact disclosure behaviours (Posey *et al.*, 2010; Krasnova, Veltri and Günther, 2012; XI Chen, Pan and Guo, 2016). There is therefore a need to elucidate if this difference is present in this digtal health context.

b) Healthcare Systems: Both countries have unique healthcare systems – the USA with its private health insurance model and Ireland with its mix of public and private healthcare. This diversity provides an opportunity to understand the role of system-level factors on self-disclosure in digital health platforms. It can help uncover how differences in access to healthcare, patient experiences, and health policies might influence self-disclosure behaviours.

c) Richer and Broader Insights: Including two countries can lead to richer and broader insights. Even with cultural similarities, there might be unique factors in each country that influence self-disclosure. By including both, this study captures a wider range of experiences, perspectives, and contextual factors. This can lead to a more comprehensive understanding of the antecedents of self-disclosure on DHPs.

3.6.1 Recruitment: survey

Prior to recruitment ethics approval was granted from the DCU research ethics committee (see APPENDIX A) and also from the Institutional Review Board at Arizona State University.

U.S. Sample: Data collection for the U.S. sample commenced during a research trip to the ASU campus in June 2018. All U.S. survey responses were collected online. Two approaches were used to gather responses. Firstly, poster adverts were placed on the ASU campus and the wider Phoenix area with information directing participants to a description of the research, a plain language statement and the survey via a QR code. Secondly, members of the biomedical informatics faculty circulated an invitation to participate email with a description of the research and a plain language statement to available email lists. 154 valid responses from the U.S. were collected, the breakdown of this sample is discussed in the quantitative analysis chapter.

Irish Sample: Data collection for the Irish sample commenced after September 2018. All Irish survey responses were collected online. Two approaches were used to gather responses. Firstly, poster adverts were placed on the DCU campus and the wider Dublin area with information directing participants to a description of the research, a plain language statement and the survey via a QR code. Secondly, snowballing technique, email lists and word of mouth recruitment of users was employed. 151 valid responses from Ireland were collected, the breakdown of this sample is discussed in the quantitative analysis chapter.

3.6.2 Recruitment: interview

In both countries the survey was used to recruit interview participants. The final question in the survey was an invitation to express interest in participating in a research interview on the same research topic. This recruitment strategy ensured that the interview sample was representative of the survey sample. Interviews were scheduled upon response to the survey. Where possible interviews happened face to face, however due to time constraints many of the U.S. interview were conducted via Zoom or Skype.

3.7 Survey

Stage one of the study involves the construction and conduction of a quantitative survey. The survey was created to test the proposed relationships in the research framework, on both Irish and American samples (Bell, Bryman and Harley, 2018).

Throughout the construction of the survey steps were taken to ensure common method bias (CMB) was removed from the survey design (Podsakoff *et al.*, 2003). Term descriptions were given for any specialised terminology, ambiguous wording was removed, anonymity was guaranteed and participants were made aware in the plain language statement that there were no right or wrong answer scenarios. Added to this statistical measures were taken to investigate CMB, this is discussed in the quantitative analysis chapter.

The survey instrument was pilot tested amongst a group of academics from Ireland and America. This group was selected as they had expertise in survey development for IS studies. Their feedback was then incorporated into a revised survey and tested once again among the group. Key aspects of this feedback included correction of negative wording in survey items, cases of ambiguity, linguistic differences between the U.S. and Ireland and the use of a seven point Likert scale.

3.7.1 Survey Structure

The survey includes measures relating to the following:

1. Technology Experience
2. Self-Disclosure
3. Trust in Health Platforms
4. Social Influence
5. Perceived Reciprocity
6. Privacy Risk Beliefs
7. Health Information Privacy Concerns
8. Personality Traits
9. Health Status
10. Demographics

3.7.2 Measurement of Variables

The following section will discuss how variables were measured in each section. All items were adapted from previously validated scales. As this was the first time many of these variables were being used in a health information context many items were reworded to fit the context. The sources for all survey items are available in the table 3.5 below.

Variable	**Source**
Technology Experience	Kim and Park, (2012)
Self-Disclosure	Posey et al. (2010) Wheeless (1978) Wheeless & Grotz (1976)
Trust in Health Platform	Sillence, Briggs, P. Harris, *et al.*, (2007); Harris, Sillence and Briggs, (2011) Li *et al.*, (2014)
Privacy Risk Beliefs	Malhorta, Kim & Argarwal (2004) Posey et al., (2010)
Perceived Reciprocity	McLure Wasko and Faraj, (2005) Kankanhalli, Tan and Wei, (2005)
Social Influence To Use Health Platform	Venktatesh et al (2003) Posey et al., (2010)
Personality Traits	Gosling, Rentfrow and Swann, (2003)
HIPC	Fox and Connolly, (2018) Hong and Thong, (2013)
Health Status	Angst and Agarwal, (2009) Harris, Sillence and Briggs,(2011)

Table 3.5 Survey item sources

Technology Experience: The opening section of the survey set out to understand participant experience with the internet and more specifically digital health platforms. Items exploring online health technology experience were adapted from previously validated items and scale (Kim and Park, 2012) and included questions such as *'I search online for information related to health management (exercise, diet, mental health, etc.)'.* In order to reflect survey design feedback, additional questions were included to examine the use of social media platforms as a source of health information sharing.

Self-Disclosure: The construct of self-disclosure was measured across five subsections as originally set out by Wheeless and Grotz, (1976, 1977). The original wording of the items was created for a non-computer mediated communication environment, as such Posey *et al.*, (2010) had set out a reworded version of the instrument to reflect an online work environment. For this study the items were reworded further to reflect the context of the research. For example, an item exploring depth of online self-disclosure of personal health information was reworded to *'I often disclose intimate, personal things about my health without hesitation online'.* Participants were then asked to indicate the depth of their disclosures across a seven point Likert scale ranging from 'strongly disagree' to 'strongly agree'. Other item options were considered for this section such as those developed by Joinson *et al.*, (2008), who have used open ended survey items and self-reporting options. However, these options are time consuming and more often used in face to face settings and where not adopted to the present study.

Trust in Health Platforms: This section explored participant perception of trust in health platforms by breaking the construct into four distinct dimensions; trust in health technology vendors; platform design; perceived reputation and information quality. The items for trust in health technology vendors were adapted from Jarvenpaa and Leidner, (1999) and has previously been employed by Posey *et al.*, (2010) in their self-disclosure study. Nine items were reworded to reflect the present study's context, for example *'I think technology vendors are always honest when it comes to using my health information'.* However, this focus on honesty, while valuable, does not fully capture trust dimensions in an online health information context as the literature on online trust emphasises issues of perceived competence and integrity (Mayer et al, 1995). For that reason, items exploring participant perceptions of design and trust were included in the trust measure in this study. These were adapted from Sillence *et al.*,(2007) and were reworded to reflect this study, with *'I trust online health platforms that are clear and easy to navigate',* as an example. Items for perceived reputation were adapted from Sillence *et al.*, (2007), with wording was updated for this study, *'I trust health technology vendors with a .org domain'.* Finally, items to measure the role of information quality in one's perception of trust in health platforms were adapted from Sillence *et al.*, (2007). An example from these reworded items being *'I trust online health platforms that provide regular information updates'.* All items within this construct were measured across a seven point Likert scale ranging from 'strongly disagree' to 'strongly agree'. Other item options where considered for this section such as technology specific items developed by McKnight, Carter and Thatcher, (2011), however as this study examines a broader trust domain these items were not used.

Social Influence: This section consists of six items, examining the role of social influence on one's propensity to trust and use a digital health platform. The items were adapted from Venkatesh *et al.*, (2003) and Posey *et al.*, (2010). The wording of items were changed to reflect the context of this study, for example *'Health care professionals would encourage me to use an online health platform'.* All items within this construct were measured across a seven point Likert scale ranging from 'strongly disagree' to 'strongly agree'. Other item options were considered such as those developed by Stibe, (2015) however these items focused on a technology's ability to socially influence its user, this study wishes to gain insight as to how other people or peer groups influence user self-disclosure therefore they were not adapted to this study.

Perceived Reciprocity: This section consists of three items adapted from Kankanhalli, Tan and Wei, (2005) and, McLure Wasko and Faraj, (2005). The items explored the role of reciprocity in one's propensity to trust and use digital health platforms. The original wording of the items was updated for the present study, *'When others disclose personal health information online, I believe that they expect me to do the same',* being an example. All items within this construct were measured across a seven point Likert scale ranging from 'strongly disagree' to 'strongly agree'. Other reciprocity items were considered however many existing items were developed for a specific health condition and the ensuing health disclosures (Wahrendorf *et al.*, 2010) while other established items where developed for face to face interviews (Pope *et al.*, 2013).

Privacy Risk Beliefs: This section consists of five items to examine participant attitudes and beliefs with regard to their general privacy when they use online platforms. The items were adapted from Malhotra, Kim and Agarwal, (2004) and have previously, successfully been employed Posey *et al.*, (2010) in an online self-disclosure context. The items' wording was updated to reflect the present study, for example *'I feel safe giving my private information to others online'.* All items within this construct were measured across a seven point Likert scale ranging from 'strongly disagree' to 'strongly agree'.

Health Information Privacy Concerns (HIPC): This section examines participant health information privacy concerns as it relates to user self-disclosures. All items were adopted directly from Fox and Connolly, (2018). Previous research by Hong and Thong, (2013) had developed items to measure internet privacy concerns and the work of Fox and Connolly (2018) subsequently adapted these items to apply in a health information context. As such no alterations have been made to the items for this study, because they have previously been used in a health information context. The HIPC measure consists of six dimensions; collection; unauthorised secondary usage; improper access; errors; control; awareness. There are a total of nineteen survey items used to cover these six dimensions. All items within this construct were measured across a seven point Likert scale ranging from 'strongly disagree' to 'strongly agree'.

Personality Traits: This section examines the Big-Five personality traits (DeYoung, Quilty and Peterson, 2007) and the influence they have on one's likelihood to self-disclose online. This section uses a novel ten item personality inventory (TIPI) of the Big-Five personality traits developed by Gosling, Rentfrow and Swann, (2003). Each item is assessed on a two-point scale. It is not possible to reach 0.7 reliability score for such a scale however due to TIPI test-retest results the items are accepted in cases where a justification can be made such as when time constraints are present or when personality is not deemed the primary topic of interest in a study (Gosling, Rentfrow and Swann, 2003). As this study has both time constraints and a primary focus on self-disclosure it is deemed justified to use the TIPI.

Demographics: Generic demographic questions were included at the end of the survey. These questions included gender, age, employment status and level of education obtained. Based on survey pilot feedback, the wording for education levels was altered to reflect the American education system and the Irish education system respectively.

3.7.2.1 Summary

The final measurement instrument consisted of ninety-one items and is shown in APPENDIX D. This survey was constructed exclusively with previously validated survey items. Some of these items were previously used in an online health context, others had already been used in an online context. All items were pilot tested with (1) a research peer group and (2) a group of individuals who used online health apps and all feedback was incorporated into the final version of the survey. These steps were taken to best assure that these items were free of errors or weaknesses commonly associated with quantitative surveys (Bell, Bryman and Harley, 2018). A number of steps were taken to confirm statistical reliability of the survey results and these steps are discussed in the quantitative analysis chapter.

3.8 Interviews

The second stage of this study involved a semi-structured interview. All interviewees were recruited via the survey and where therefore familiar with the study. The purpose of the interviews was to develop deeper insights into the role of each construct as they relate to self-disclosure, trust of digital health platforms and HIPC. A total of 20 interviews were conducted, 10 interviews with American participants and 10 interviews with Irish participants. 5 of the American interviews took place in a private room of the library on the ASU Tempe campus. The remaining 5 American interviews were conducted over Zoom and Skype due to the researchers limited time in the U.S. All 10 of the Irish interviews took place in a private booked room on the DCU campus. Interviews lasted between 30-60 minutes. All participants were given a plain language statement to read prior to the interview. All participants were asked to sign a research consent form prior to the commencement of the interview and all were informed that they could stop the interview at any time, should they wish.

The interviews were semi structured and followed a broad guide (see APPENDIX E) developed from the same sections as the survey; technology experience; self-disclosure; trust in health platforms; social influence; perceived reciprocity; privacy risk beliefs; HIPC; personality; demographics. The guide was pilot tested with a research peer group and was reviewed to eliminate ambiguous wording and unclear terminology. While the interview questions were developed from the survey additional questions were added to each section in an effort to open up the topic and gain deeper insight (Bell, Bryman and Harley, 2018; Seale, 2018). As a result, introductory, follow-up and probing questions were utilised when necessary.

In an effort to ensure valid data collection and analysis all interviews were recorded and all interview rooms were checked for suitability, lack of noise pollution and comfort (Bell, Bryman and Harley, 2018; Seale, 2018). In addition, participants were allowed time to finish answers and to clarify comments where necessary. Analytical techniques, findings and validation methods are discussed in the qualitative analysis chapter.

3.9 Chapter Summary

This chapter has provided an outline of the underlying philosophical paradigm of this research study, the chosen research method and its accompanying strategy. Both quantitative and qualitative methods have been presented as has the predominant philosophical paradigm associated with both. After this the mixed methods research approach has been presented along with its predominant philosophical paradigm; pragmatism. With this a justification was been made for the use of a mixed methods research approach guided by a pragmatic outlook.

A triangulated research design strategy has been discussed as has the construction of a quantitative survey and the subsequent qualitative interview. Clear guidelines for sampling, recruitment, collection and analysis based on tried and tested procedures (O'Cathain, Murphy and Nicholl, 2008; Creswell and Plano Clark, 2011; Venkatesh, Brown and Sullivan, 2016; Bell, Bryman and Harley, 2018; Seale, 2018) have been adhered to at all times. The next two chapters provide discussion on the quantitative and qualitative analyses and findings as well as methods for data validation.

4 Chapter Four: Quantitative Analysis

4.1 Introduction

This chapter provides analysis and detailed insight to the quantitative data that was gathered for this study. The chapter structure is laid out in the Figure 4.1. Firstly, the chapter discusses the sample response rates and the general data screening that was performed in the preliminary considerations section. The sample responses are then split into Irish and U.S. citizen datasets, and the characteristics of the two datasets are explored. The research framework, introduced in previous chapter (3) and developed in the literature review is tested. In the measurement model assessment and structural model assessment sections, the model is discussed in terms of reliability and validity, factor structure and proposed relationships. The chapter concludes with an overview of the hypotheses and quantitative results.

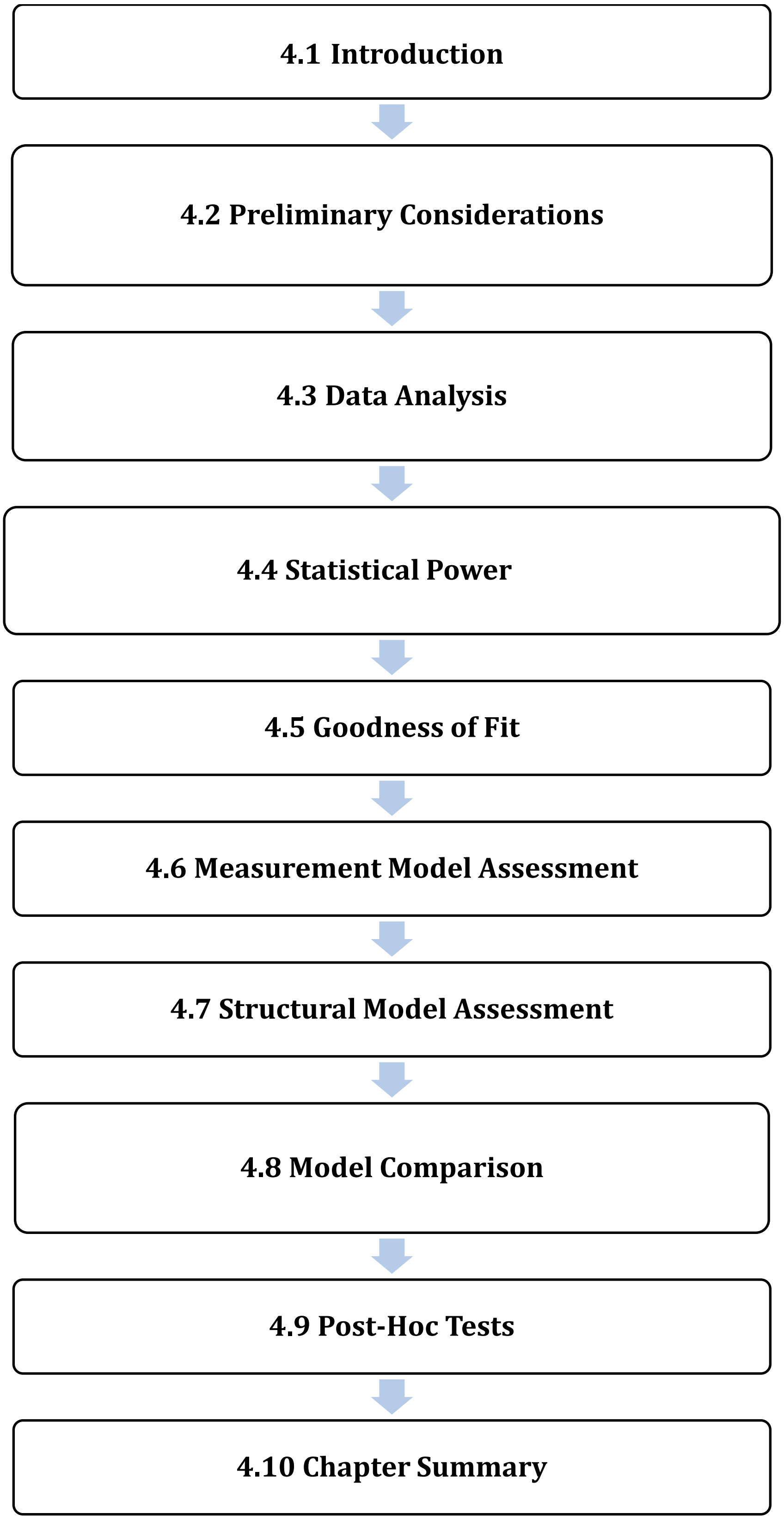


Figure 4.1 Chapter Structure

4.2 Research Model

This research set out to examine self-disclosure. It identified 2 key constructs which merited attention both in terms of their potential effect on self-disclosure, as well as their potential inter-relationships and how these effected the disclosure outcome, and in terms of the factors which influence their expression. The research model and relationships under examination are shown in figure 4.2.

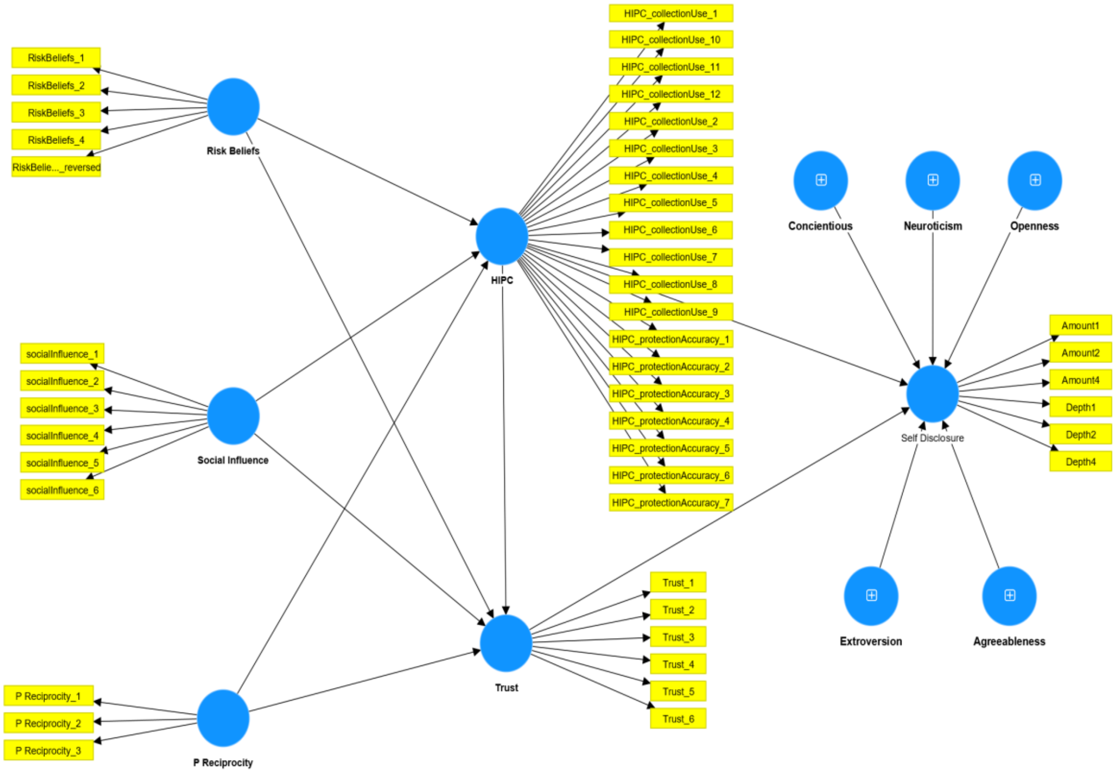


Figure 4.2 Research Model

The relationship hypotheses are as follows:

H1: In a DHP context, HIPC will reduce self-disclosure behaviour.

H2: In a DHP context, THP will increase self-disclosure behaviour.

H3: In a DHP context, HIPC will reduce THP.

H4: In a DHP context, privacy risk beliefs will increase HIPC.

H5: In a DHP context, privacy risk beliefs will reduce THP.

H6: In a DHP context, perceived reciprocity will increase THP.

H7: In a DHP context, perceived reciprocity reduces HIPC.

H8: In a DHP context, social influence will increase THP.

H9: In a DHP context, social influence will reduce HIPC.

H10: In a DHP context, an individual's agreeableness will increase their self-disclosure

H11: In a DHP context, an individual's conscientiousness will decrease their self-disclosure.

H12: In a DHP context, an individual's openness will increase their self-disclosure.

H13: In a DHP context, an individual's extroversion will increase their self-disclosure.

H14: In a DHP context, an individual's neuroticism will increase their self-disclosure.

4.3 Data analysis

4.3.1 Data Screening

Before any model can be tested, it is necessary for all collected data to be screened and cleaned. This section discusses that process and the protocol for cleaning the data as well as assessing missing data and outliers.

4.3.2 Addressing Missing Data

Upon receiving all survey responses, the completeness of the survey questionnaires and eligibility of respondents were checked by the researcher. Following this, it was necessary to clean and screen data to ensure that the assumptions of multivariate analysis were satisfied (Hair *et al.*, 2010). To this effect Hair et al., (2010) outline a four-step process to address missing data which was employed in this study. The first step is to ascertain whether incidents of missing data are ignorable or non-ignorable, such as when some participants omit a response to a question that does not concern them. The second step involves understanding the extent of missing data, for example if a respondent were to leave 15% of the survey with missing data, that response would have to be entirely omitted (Hair, J. F., Ringle, C. M., & Sarstedt, 2014). The third step is to understand the randomness of missing data using missing value analysis in SPSS. As no significant findings were found, any missing data was considered missing completely at random. Finally, the fourth step deals with imputation, or replacing missing data with substitute data where possible. As the survey used in this study required all participants to complete all questions, save for questions relating to employment or education status, none of the four steps outlined reached any degree of concern.

4.3.3 Identifying Outliers

The next step in accordance with Hair *et al.*, (2010) is to identify outliers. Outliers must be examined as they might have influential and negative effects on the result of data analysis (Hair *et al.*, 2010). Any instance considered abnormal was reviewed on a case by case bases. One instance of response was deemed abnormal but the issue was rectified by reversing item codes. This was done in accordance with Hair *et al.,* (2010) in an effort to retain data where possible.

4.3.4 Sample Response Rates

This section discusses the study response rates, split into Irish and U.S. user cohorts. As previously discussed, three distinct ages groups are prevalent in the datasets. The first group is 18-24, most of whom are in college or are recently graduated. This group are tech savvy and express low online self-disclosure relating to health. The second group consists of users aged 25-49. These individuals are employed across different industries and also express tech savviness. The final group consists of users aged 50 and older who are either employed or retired. These users express slightly higher levels of online self-disclosures relating to health.

Responses: Irish Sample

All Irish survey responses were collected online. Two approaches were used to gather responses. Firstly, poster adverts were placed on the DCU campus and the wider Dublin area with information directing participants to the survey via a QR code. Secondly, snowballing technique, email lists and word of mouth recruitment of users was employed.

Responses: U.S. Sample

All U.S. survey responses were collected online. Two approaches were used to gather responses. Firstly, poster adverts were placed on the ASU campus and the wider Phoenix area with information directing participants to the survey via a QR code. Secondly, members of the biomedical informatics faculty circulated an invitation to participate email to available email lists.

4.3.5 Sample Profile

Profile: Irish Sample

Of the 151 responses received, 54% of respondents were male and 46% were female. Respondents registered as students at the time accounted for 40%, while 49.3% were employed/self-employed, the remaining 9.3% were homemakers or retired. Regarding ages groups, 36.7% were aged 18-24, 39.3% were aged 25-49, the final group 50 and above, made up the remaining 24%. Distribution of education was as follows; 16.7% completed secondary school, 52.7% had an undergraduate/bachelor's degree, 24.7% had a Master's degree and 4% had completed further advanced studies, such as PhD. 44.7% of respondents had more than 15 years of internet experience, while 32.7% reported having 10-15 years of internet experience, 20% reported having 5-10 years of internet experience, with only 2.7% reporting 1-5 years' internet experience. This indicated high levels of technical familiarity and literacy.

With regard to health status, 2% of respondents considered themselves to have poor health, 11.3% of respondents considered themselves to have fair health, 38% of respondents considered themselves to have good health, 38% of respondents considered themselves to have very good health, and 10.7% of respondents considered themselves to have excellent health. A further 19.9% reported having a chronic illness A total of 26.7% of respondents reported having an illness that periodically impacted their lives, 12% of respondents reported having a sensitive illness, with 8.7% opting not say.

In relation to how respondents use the internet, social media platforms and mobile applications for health information exchange, the following can be said; most respondents, that is 92.7% of respondents, use the internet to seek health information online, be it fitness, diet, mental health or disease diagnosis information. 55.3% of respondents use the internet to purchase health food and medical equipment. 49.3% of respondents reported using social media platforms and applications for health information exchange, while 80% of respondents use a fitness app. 64.7% of respondents reported using a diet or calorie tracking app. 18% of respondents reported using blood pressure monitoring applications while 6.7% have used a diabetes application. 10.7% have used a pregnancy related app, while 19.3% of respondents reported using a sleep tracking application. Mood monitoring applications were used by 19.3% of respondents, 18% of respondents have used personal health record systems, and finally 46.7% of respondents reported using health information sites such as WebMD. Table 4.1, below displays respondents use of DHPs and the internet for health information exchange.

Digital Platforms and websites for health	**% use by Irish respondents**
Internet for health information exchange	92%
Social media for health information exchange	49.3%
Fitness trackers	80%
Diet apps	64.7%

Blood pressure monitoring apps	18%
Diabetes apps	6.7%
Pregnancy apps	10.7%
Sleep apps	19.3%
Mood monitoring apps	19.3%
Personal health record	18%
Online heath communities (e.g. WebMD)	46.7%

Table 4.1 DHPs Ireland

Profile: U.S. Sample

Of the 154 responses received, 52.4% of respondents were male, 46.3% were female and 1.4% identified as 'Other'. Respondents registered as students at the time accounted for 11.6%, while 78.9% were employed/self-employed, the remaining 6.8% were homemakers or retired. Regarding ages groups, 10.2% were aged 18-24, 74.8% were aged 25-49, the final group 50 and above, made up the remaining 14.9%. Distribution of education was as follows; 8.2% completed high school, 64.6% had an undergraduate/bachelor's degree, 22.4% had a Master's degree and 4.8% had studied beyond a Master's.

When technical experience was examined, most respondents (66.7%) reported having more than 15 years' internet experience, while 19% reported having 10-15 years' internet experience, 11.6% reported having 5-10 years of internet experience, with only 2.7% reporting 1-5 years' internet experience.

Regarding health status, 2% of respondents considered themselves to have poor health, 11.6% of respondents considered themselves to have fair health, 33.3% of respondents considered themselves to have good health, 34.7% of respondents considered themselves to have very good health, and a further 18.4% of respondents considered themselves to have excellent health. Of these, 20.4% reported having a chronic illness, 21.1% of respondents reported having an illness that periodically impacted their lives, 12.9% of respondents reported having a sensitive illness, with 24.6% opting not to say.

With regard to how respondents use the internet, social media platforms and mobile applications for health information exchange the following can be said; 94.6% of respondents use the internet to seek health information online, be it fitness, diet, mental health or disease diagnosis information. 78.2% of respondents purchase health food and medical equipment online. 64.6% of respondents reported using social media platforms for health information exchange, while 76.72% of respondents use a fitness app. 63.9% of respondents reported using a diet or calorie tracking app. 38.1% of respondents reported using blood pressure monitoring applications while 18.4% have used a diabetes application. 22.4% have used a pregnancy related app, while 42.2% of respondents reported using a sleep tracking application. Mood monitoring applications were used by 27.9% of respondents, 36.1% of respondents have used personal health record systems, and finally 68% of respondents reported using health information sites such as WebMD. Table 4.2, below displays respondents use of DHPs and the internet for health information exchange.

Digital Platforms and websites for health	**% use by American respondents**
Internet for health information exchange	94.6%
Social media for health information exchange	64.6%
Fitness trackers	76.72%
Diet apps	63.9%
Blood pressure monitoring apps	38.1%
Diabetes apps	18.4%
Pregnancy apps	22.4%
Sleep apps	42.2%
Mood monitoring apps	27.9%
Personal health record	36.1%
Online heath communities (e.g. WebMD)	68.7%

Table 4.2 DHPs America

4.4 Statistical Power

The research model was tested using Partial Least Squares (PLS) Structural Equation Modelling (SEM) as implemented in SmartPLS (Hair *et al.*, 2019). PLS-SEM is appropriate when the objective is to identify key driver constructs in a relatively complex model that simultaneously deals with multiple latent variables and relationships, without being subject to rigorous distributional assumptions (Hair et al., 2017). The sample size was estimated based on the power analysis as provided by Cohen, (1992) and Cohen *et al.*, (2003). We use GPower (Buchner *et al.*, 2014), following the procedure delineated by Faul *et al.*, (2009) considering the model requires the maximum of seven predictors, and a statistical power of 90% under a statistical significance of 1% for an expected medium effect size, resulting a minimum sample size of n=171.

4.5 Goodness-of-fit

The goodness of fit of the models were analysed using minimum discrepancy (cmin/df:), comparative fit index (CFI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR). The metrics were as follows: cmin/df: 1.45, CFI: 0.545b RSMEA: 0.070, SRMR: 0.032, indicating good fit. These metrics met the recommendations of Hair *et al*., (2010), for good fit for number of variables and sample size. A normal distribution was assumed for the model. Since simultaneous examination of endogenous and exogenous variables could result in common method bias (CMB), the guidance of Podsakoff *et al*., (2003) was followed. Accordingly, survey items were tested to remove any ambiguity prior to administration of the survey. The survey items were randomised and respondents were made aware that there were no right or wrong answers. Common latent factors were included and tested for standardized regression weight both prior and post addition of these latent factors (Gaskin, 2012). No major change was evident when comparing these standardized regression weights and the validity and reliability thresholds were satisfied.

4.6 Measurement Model Assessment

To test the reliability of each item, factor loadings were measured. Hair *et al*., (2019) advise threshold values equal to or greater than 0.7 are considered reliable when assessing item loadings. In addition, Cronbach's Alpha and composite reliability values should be equal to or greater than 0.7, (Raykov, 1997). A fourth assessment, average variance extracted (AVE), a common measure for establishing the convergent and discriminant validity is also performed. A value of 0.5 or greater for AVE means that the given construct explains for more than half the variance of its items (Hair *et al*., 2019). As shown in Table 4.3, all loadings are equal to or greater than 0.7.

	Privacy Risk Beliefs	Social Influence	P Reciprocity	HIPC	THP	Self Disclosure
RiskBeliefs_1	0.840	-0.299	-0.226	0.395	-0.344	-0.249
RiskBeliefs_2	0.785	-0.218	-0.166	0.524	-0.351	-0.108
RiskBeliefs_3	0.841	-0.327	-0.183	0.494	-0.414	-0.148
RiskBeliefs_4	0.853	-0.301	-0.172	0.452	-0.314	-0.155
RiskBeliefs_5_reversed	0.688	-0.566	-0.529	0.283	-0.609	-0.595
socialInfluence_1	-0.412	0.874	0.451	-0.176	0.513	0.502
socialInfluence_2	-0.394	0.883	0.427	-0.163	0.499	0.466
socialInfluence_3	-0.374	0.805	0.449	-0.181	0.422	0.452
socialInfluence_4	-0.322	0.779	0.346	-0.201	0.513	0.367
socialInfluence_5	-0.258	0.691	0.477	-0.197	0.446	0.445
socialInfluence_6	-0.272	0.685	0.408	-0.146	0.377	0.346
P Reciprocity_1	-0.159	0.389	0.825	-0.000	0.352	0.401
P Reciprocity_2	-0.255	0.436	0.854	-0.098	0.405	0.420
P Reciprocity_3	-0.359	0.517	0.873	-0.168	0.574	0.584
HIPC_collectionUse_1	0.423	-0.193	-0.054	0.767	-0.265	-0.039
HIPC_collectionUse_10	0.438	-0.256	-0.199	0.830	-0.353	-0.148
HIPC_collectionUse_11	0.434	-0.163	-0.055	0.850	-0.296	-0.061
HIPC_collectionUse_12	0.399	-0.148	-0.160	0.798	-0.237	-0.102
HIPC_collectionUse_2	0.481	-0.231	-0.127	0.874	-0.335	-0.081
HIPC_collectionUse_3	0.425	-0.195	-0.081	0.798	-0.266	-0.030
HIPC_collectionUse_4	0.447	-0.185	-0.135	0.824	-0.268	-0.149
HIPC_collectionUse_5	0.351	-0.185	-0.096	0.767	-0.259	-0.140
HIPC_collectionUse_6	0.418	-0.103	-0.063	0.774	-0.239	-0.068
HIPC_collectionUse_7	0.356	-0.137	-0.066	0.719	-0.194	-0.071
HIPC_collectionUse_8	0.437	-0.205	-0.156	0.832	-0.335	-0.132
HIPC_collectionUse_9	0.399	-0.149	-0.149	0.631	-0.153	-0.188
HIPC_protectionAccuracy_1	0.477	-0.179	-0.092	0.828	-0.287	-0.119
HIPC_protectionAccuracy_2	0.470	-0.223	-0.100	0.851	-0.334	-0.112
HIPC_protectionAccuracy_3	0.466	-0.170	-0.081	0.825	-0.346	-0.137
HIPC_protectionAccuracy_4	0.445	-0.184	-0.047	0.836	-0.267	-0.106

HIPC_protectionAccuracy_5	0.477	-0.168	-0.099	0.848	-0.322	-0.079
HIPC_protectionAccuracy_6	0.419	-0.176	-0.069	0.763	-0.312	-0.094
HIPC_protectionAccuracy_7	0.416	-0.154	-0.019	0.798	-0.255	-0.052
Trust_1	-0.336	0.529	0.437	-0.254	0.721	0.360
Trust_2	-0.488	0.478	0.488	-0.299	0.842	0.483
Trust_3	-0.389	0.479	0.481	-0.303	0.815	0.422
Trust_4	-0.380	0.449	0.390	-0.214	0.764	0.269
Trust_5	-0.310	0.392	0.304	-0.269	0.729	0.267
Trust_6	-0.503	0.464	0.446	-0.328	0.861	0.416
Amount1	-0.227	0.424	0.457	-0.047	0.350	0.832
Amount2	-0.299	0.542	0.493	-0.085	0.448	0.849
Amount4	-0.278	0.511	0.453	-0.076	0.399	0.873
Depth1	-0.250	0.415	0.481	-0.124	0.394	0.860
Depth2	-0.278	0.446	0.528	-0.163	0.445	0.874
Depth4	-0.298	0.478	0.529	-0.141	0.429	0.887

Table 4.3 Cross Loadings

Discriminant validity was tested via Cronbach's Alpha and composite reliability values, which are greater than 0.7, and AVE values, which are greater than 0.5. Discriminant validity was further tested by comparing the square root of AVE and the correlation between each set of constructs. Table 2 shows that all variables are discriminate as the intercorrelation values are less than the square root of the AVE for each construct. The variance inflation factor (VIF), a measure of multicollinearity in a least squares regression analysis, of the model is 1.676. As such, the constructs' convergent validity is established.

	Cronbach's Alpha	Composite Reliability	AVE	1	2	3	4	5	6
1- Self Disclosure	0.931	0.946	0.744	0.862					
2- HIPC	0.969	0.971	0.644	-0.125	0.803				
3- P Reciprocity	0.818	0.887	0.724	0.570	-0.122	0.851			
4- Privacy Risk Beliefs	0.861	0.901	0.646	-0.317	0.539	-0.323	0.804		
5- Social Influence	0.877	0.908	0.624	0.546	-0.225	0.537	-0.432	0.79	
6- Trust	0.879	0.909	0.625	0.479	-0.354	0.545	-0.515	0.59	0.791

VIF (highest value) = 1.676

Table 4.4 Discriminant validity

4.7 Structural Model Assessment

Figure 4.3 shows the results obtained for the full data set (combined Irish and USA data)

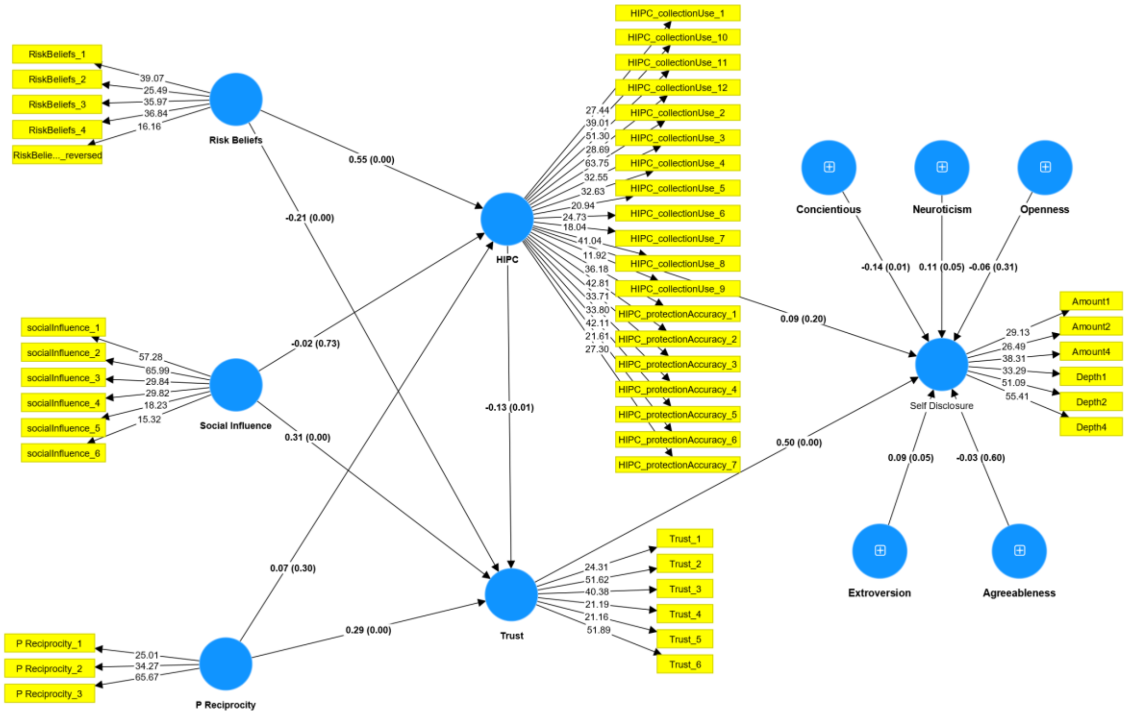


Figure 4.3 Structural Model – Full Data Sample

The higher effects observed in the model are the paths from Privacy Risk Beliefs to HIPC (f^2=0.344) and THP to Self-Disclosure (f^2 = 0.297) which are close to the threshold of 0.35 to be considered a large effect. In the same vein, Social Influence to THP (0.123) and Perceived Reciprocity to THP (0.119) are both close to the 0.15

threshold of medium effect size, while the path from Privacy Risk Beliefs to THP may be considered small-medium effect size (Cohen, 1988).

Construct	R^2
HIPC	0.29
THP	0.50
Self-Disclosure	0.29

Table 4.5 R^2. Results

Although Goodness-of-fit index (GoF) was earlier proposed as a solution to validate the model globally (Tenenhaus *et al.*, 2005), it subsequently has been challenged both conceptually and empirically (Henseler and Sarstedt, 2013) among other reasons because it does not penalize the over-parametrization of the model. In consequence, following the recommendations of Hair *et al.*, (2017), we instead assess the Standardized Root Mean Square Residual (SRMR), which is defined as the root mean square discrepancy between the observed correlations and the model-implied correlations. As this index is an absolute measure of fit, the lowest value possible is considered the better, since this measure implies that the model has a good fit with the data. Although PLS authors advise researchers not to emphasize fit indicators against the predictive power of the model, given the predictive nature of the PLS algorithm, we still report the above model fit index SRMR = 0.080, which is considered a good fit even when compared with the more restrictive threshold of 0.08 traditionally applied in the context of CB-SEM (Hu and Bentler, 1999).

4.8 Cross Cultural Comparison

As a core objective of this research is to provide a cross cultural examination of factors influencing self-disclosure on digital health platforms, for that reason a more granular examination was undertaken, focusing on individual samples and their results in relation to the research mode. For that reason, two models were used in this analysis: one with an U.S. cohort and one with an Irish cohort. The results of each of these models will be discussed separately then compared.

4.8.1 Irish Model

The Irish model (figure 4.4) had a strong explanatory power with regard to the relationships of the constructs. Hypotheses were tested among the Irish sample of respondents (N = 151) using AMOS 24. For the purpose of distinguishing hypotheses and findings between both samples, the letter ‘a’ is used in relation to hypotheses for the Irish sample and the letter ‘b’ is used in relation to hypotheses for the USA sample.

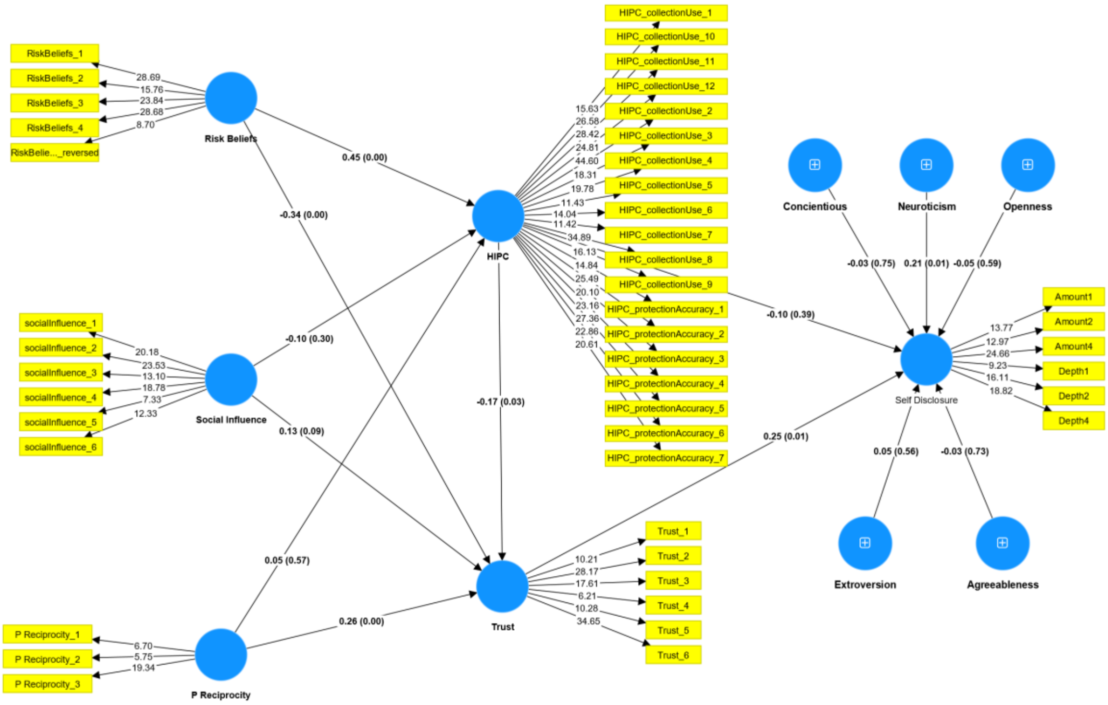


Figure 4.4 Structural Results for Irish Sample

Construct	R^2
HIPC	0.23
THP	0.46
Self-Disclosure	0.15

Table 4.6 R^2 Results - Ireland

HIPC

H1a proposed that HIPC was negatively correlated with self-disclosure. The path analysis revealed a negative relationship however it was not significant, rejecting H1a (β=-0.10, P = 0.39). H3a proposed a negative relationship between HIPC and THP. The path analysis revealed a significant, negative relationship (β=-0.17, P – 0.03), supporting H3a.

THP

H2a proposed a positive relationship between trust in health platforms and self-disclosure. This path analysis demonstrated a strong, positive support for H2a (β=0.25, P = 0.01).

Privacy Risk Beliefs

H4a proposed a positive association between privacy risk beliefs and HIPC. This path analysis revealed a strong positive relationship between privacy risk beliefs and HIPC (β=0.45, P < 0.001), supporting H4a. H5a proposed that privacy risk beliefs are negatively correlated with THP. The path analysis revealed the expected negative, significant relationship between privacy risk beliefs and THP (β=-0.34, P < 0.001), supporting H5a.

Perceived Reciprocity

H6a posited that perceived reciprocity would positively impact THP. The path analysis revealed the expected positive relationship between perceived reciprocity and THP, (β=0.26, P < 0.001), supporting H6a. H7a proposed a negative relationship between perceived reciprocity and HIPC. The path analysis for this relationship was not significant, nor positive/negative, rejecting H7a (β0.05, P = 0.57).

Social Influence

H8a proposed that social influence and THP were positively correlated. The path analysis did reveal a positive relationship however it was not significant, therefore rejecting H8a (β=0.13, P = 0.09). H9a proposed a negative association between social influence and HIPC. This path analysis was negative however it was not significant, thereby rejecting H9a (β-0.10, P = 0.32).

Personality Traits

None of H10a (positive correlation between agreeableness and self-disclosure), H11a, (negative correlation between conscientiousness and self-disclosure), H12a (positive correlation between openness and self-disclosure), or H13a (positive correlation between extroversion and self-disclosure), were shown to be have signification path analysis relationships (β=-0.03, P = 0.74; β=-0.03, P = 0.74; β= -0.05, P = 0.58; β=0.05, P = 0.55). H14a, posited a positive correlation between neuroticism and self-disclosure. This path analysis was found to be both evident and significant (β=0.21, P = 0.01).

As shown in table 4.7, the findings support many of the proposed relationships. To assess how much the variables explained the outcome of the study, R^2 was analysed. These findings resulted in a R^2 of 0.23 for health information privacy concern, meaning privacy risk beliefs, social influence and perceived reciprocity can explain HIPC by 23%. An R^2 of 0.46 for trust in online health platforms was found, meaning privacy risk beliefs, social influence and perceived reciprocity can explain trust in online health platforms by 46%. An R^2 0.15 for self-disclosure, meaning trust in online health platforms can explain self-disclosure in an online health context by 15%.

Hypotheses	**Variables**	**Supported**
H1a: In a DHP context, HIPC will reduce self-disclosure behaviour	HIPC → SD	**X**
H2a: In a DHP context, THP will increase self-disclosure behaviour	THP → SD	✓**
H3a: In a DHP context, HIPC will reduce THP	HIPC → THP	✓*
H4a: In a DHP context, privacy risk beliefs will increase HIPC	RB → HIPC	✓***
H5a: In a DHP context, privacy risk beliefs will reduce THP	RB → THP	✓***
H6a: In a DHP context, perceived reciprocity will increase THP	PR → THP	✓***
H7a: In a DHP context, perceived reciprocity reduces HIPC	PR → HIPC	**X**
H8a: In a DHP context, social influence will increase THP	SI → THP	**X**

H9a: In a DHP context, social influence will reduce HIPC	SI → HIPC	**X**
H10a: In a DHP context, an individual's agreeableness will increase their self-disclosure	AGREE → SD	**X**
H11a: In a DHP context, an individual's conscientiousness will decrease their self-disclosure	CONSCI. → SD	**X**
H12a: In a DHP context, an individual's openness will increase their self-disclosure	OPEN. → SD	**X**
H13a: In a DHP context, an individual's extroversion will increase their self-disclosure	EXTRO. → SD	**X**
H14a: In a DHP context, an individual's neuroticism will increase their self-disclosure	NEURO. → SD	✓**

Table 4.7 Irish Model Findings

✓ Supported at the .10 level, ✓* Supported at 0.05 level, ✓** Supported at the .01 level, ✓*** Supported at .001 level, **X** not supported

4.8.2 U.S. Model

Hypotheses were tested among the USA Sample of respondents (N = 154) using AMOS 24. This model (figure 4.5) provided strong explanatory power for the relationship between several of the constructs.

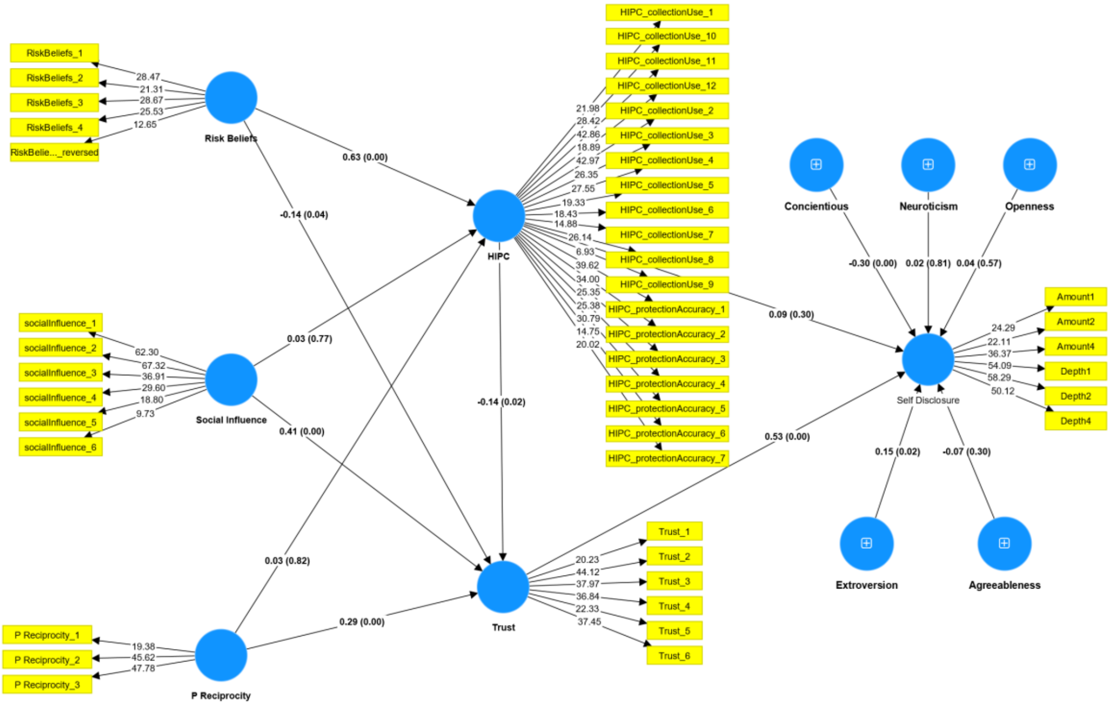


Figure 4.5 Structural Results for USA Sample

Construct	R^2
HIPC	0.38
THP	0.56
Self-Disclosure	0.46

Table 4.8 R^2 Results - America

HIPC

H1b proposed that HIPC was negatively correlated with self-disclosure. The path analysis was revealed to be not significant, rejecting H1b (β=0.09, P = 0.37). H3b proposed a negative relationship between HIPC and THP. This path analysis was shown to be negative and significant (β=-0.14, P -0.03), therefore supporting H3b.

THP

H2b posited a positive relationship between trust in health platforms and self-disclosure. The path analysis demonstrated a strong, positive relationship, therefore supporting H2b (β=0.53, P < 0.001).

Privacy Risk Beliefs

H4b proposed a positive association between privacy risk beliefs and HIPC. This path analysis presented a strong, positive relationship for H4b (β=.63, P < 0.001), therefor supporting H4b. H5b proposed that privacy risk beliefs are negatively correlated with THP. The path analysis for H5b showed a strong, negative relationship (β=-0.14, P=0.04), supporting H5b.

Perceived Reciprocity

H6b posited that perceived reciprocity would positively impact THP. The path analysis revealed a positive, strong relationship between perceived reciprocity and THP (β=0.29, P < 0.001), supporting H6b. H7b proposed a negative relationship between perceived reciprocity and HIPC. This path analysis did not reveal significant, nor positive/negative relationship, rejecting H7b (β=0.03, P = 0.81).

Social Influence

H8b proposed that social influence and THP were positively correlated. The path analysis revealed a significant, positive relationship supporting H8b ($\beta=0.41$, $P < 0.001$). H9b proposed a negative association between social influence and HIPC. This path analysis was not significant thereby rejecting H9b ($\beta=0.03$, $P = 0.77$).

Personality Traits

None of H10b (positive correlation between agreeableness and self-disclosure), H12b (positive correlation between openness and self-disclosure), or H14b (negative correlation between neuroticism and self-disclosure), were shown to be significant relationships ($\beta=-0.07$, $P = 0.27$; $\beta=0.04$, $P = 0.55$; $\beta=0.02$, $P = 0.79$). H11b proposed a negative correlation between conscientiousness and self-disclosure. Its path analysis revealed a strong negative relationship ($\beta=-0.30$, $P < 0.001$), supporting H11b. H13b proposed a positive correlation between extroversion and self-disclosure. Its path analysis revealed a strong, positive relationship existed ($\beta=0.15$, $P = 0.01$), therefore supporting H13b.

As shown in table 4.8, the findings support many of the proposed relationships. To access how much the variables explained the outcome of the study, R^2 was analysed. These findings resulted in a R^2 of 0.38 for health information privacy concern, meaning privacy risk beliefs, social influence and perceived reciprocity can explain HIPC by 38%. An R^2 0.56 for trust in online health platforms, meaning privacy risk beliefs, social influence and perceived reciprocity can explain trust in online health platforms by 56%. An R^2 0.46 for self-disclosure, meaning trust in online health platforms can explain self-disclosure in an online health context by 46%.

Hypotheses	**Variables**	**Supported**
H1b: In a DHP context, HIPC will reduce self-disclosure behaviour	HIPC → SD	**X**
H2b: In a DHP context, THP will increase self-disclosure behaviour	THP → SD	✓***
H3b: In a DHP context, HIPC will reduce THP	HIPC → THP	✓*
H4b: In a DHP context, privacy risk beliefs will increase HIPC	RB → HIPC	✓***
H5b: In a DHP context, privacy risk beliefs will reduce THP	RB → THP	✓**
H6b: In a DHP context, perceived reciprocity will increase THP	PR → THP	✓***
H7b: In a DHP context, perceived reciprocity reduces HIPC	PR → HIPC	**X**
H8b: In a DHP context, social influence will increase THP	SI → THP	✓***
H9b: In a DHP context, social influence will reduce HIPC	SI → HIPC	**X**
H10b: In a DHP context, an individual's agreeableness will increase their self-disclosure	AGREE → SD	**X**
H11b: In a DHP context, an individual's conscientiousness will decrease their self-disclosure	CONSCI. → SD	✓***
H12b: In a DHP context, an individual's openness will increase their self-disclosure	OPEN. → SD	**X**

H13b: In a DHP context, an individual's extroversion will increase their self-disclosure	EXTRO. → SD	✓**
H14b: In a DHP context, an individual's neuroticism will increase their self-disclosure	NEURO. → SD	**X**

Table 4.9 U.S. Model: Findings

✓ Supported at the .10 level, ✓* Supported at 0.05 level, ✓** Supported at the .01 level, ✓*** Supported at .001 level, **X** not supported

4.9 Post-Hoc Tests

4.9.1 Model Comparison

The two models were compared using permutation analysis and a MICOM multigroup analysis. The permutation analysis was achieved by performing a data permutation between the sample groups. The MICOM multigroup analysis was done following the 3 steps outlined in the SmartPLS documentation. These steps included analysing the configural invariance, compositional invariance and finally, the equality of composite mean values and variances.

The results of the permutation analysis by country, showing compositional invariance results can be seen in Table 4.10.

	Original Correlation	Correlation Permutation Mean	Permutation p-Values	Configural Invariance	Compositional Invariance
HIPC	0.999	0.999	0.498	Yes	Yes
P Reciprocity	0.985	0.997	0.018	Yes	No
Privacy Risk Beliefs	0.997	0.999	0.064	Yes	Yes
Self-Disclosure	0.999	0.999	0.160	Yes	Yes
Social Influence	0.997	0.998	0.286	Yes	Yes
THP	0.998	0.999	0.054	Yes	Yes

Table 4.10 MICOM Permutation test – by Country

The results show that partial measurement invariance was established for all constructs other than perceived reciprocity. This enabled further path coefficient comparison. That analysis (Table 4.11) revealed four path differences between the two models – observed at the 5% significant level - with path difference being calculated as Irish model values subtracted from U.S. model values. The path differences included privacy risk beliefs to trust in DHPs (path difference: 0.196; P = 0.049), social influence to trust in DHPs (path difference: 0.283; P = 0.012), conscientiousness to self-disclosure (path difference: -0.275; P = 0.018), and trust in DHPs to self-disclosure (path difference: 0.280; P = 0.012).

	Path differences Country(1.0) - Country(2.0)	pvalues Country(1.0) - Country(2.0)	Sig
Agreeableness -> Self Disclosure	-0.037	0.725	
Conscientious -> Self Disclosure	-0.275	0.018	Yes
Extroversion -> Self Disclosure	0.105	0.304	
HIPC -> Self Disclosure	0.190	0.144	
HIPC -> THP	0.035	0.728	
Neuroticism -> Self Disclosure	-0.189	0.097	
Openness -> Self Disclosure	0.094	0.433	
P Reciprocity -> HIPC	-0.024	0.857	
P Reciprocity -> THP	0.023	0.840	
Privacy Risk Beliefs -> HIPC	0.186	0.097	
Privacy Risk Beliefs -> THP	0.196	0.049	Yes
Social Influence -> HIPC	0.137	0.368	
Social Influence -> THP	0.283	0.012	Yes
THP -> Self Disclosure	0.280	0.012	Yes

Table 4.11MGA test - Comparing Path coefficients between Country groups

Gender

In order to determine whether gender-based differences might have influenced the construct relationships and outcomes, the model relationships were further examined in that regard.

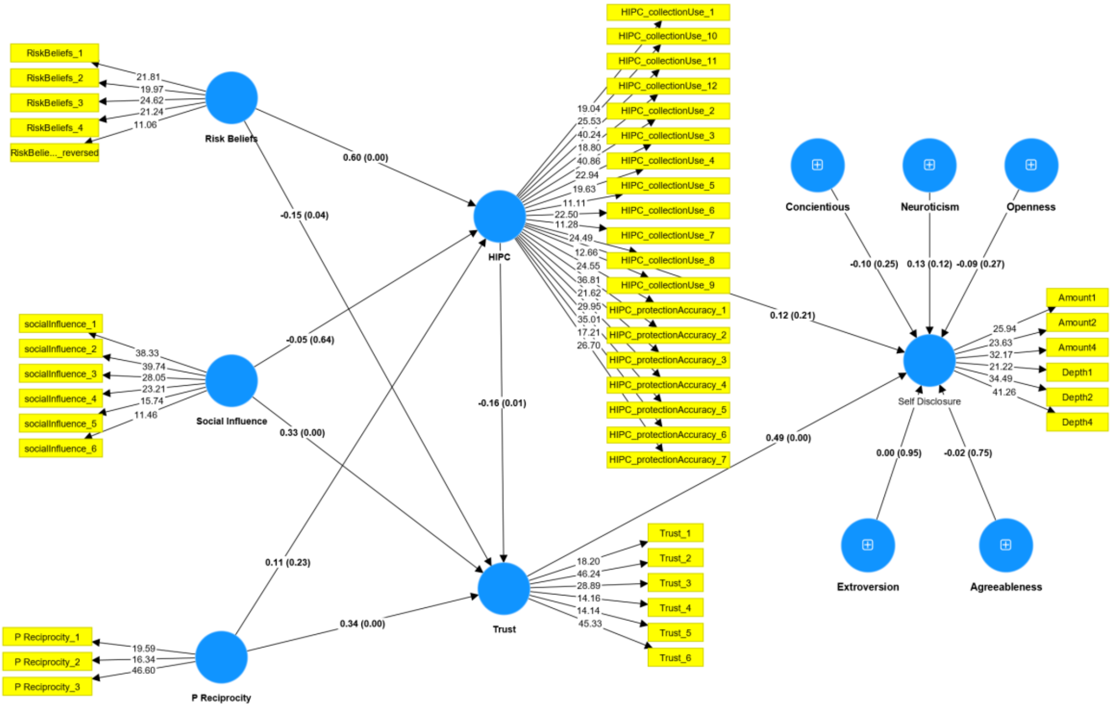


Figure 4.6 Structural Results: Males (n=160)

Construct	R^2
HIPC	0.35
THP	0.55
Self-Disclosure	0.30

Table 4.12 R^2 Results - Male

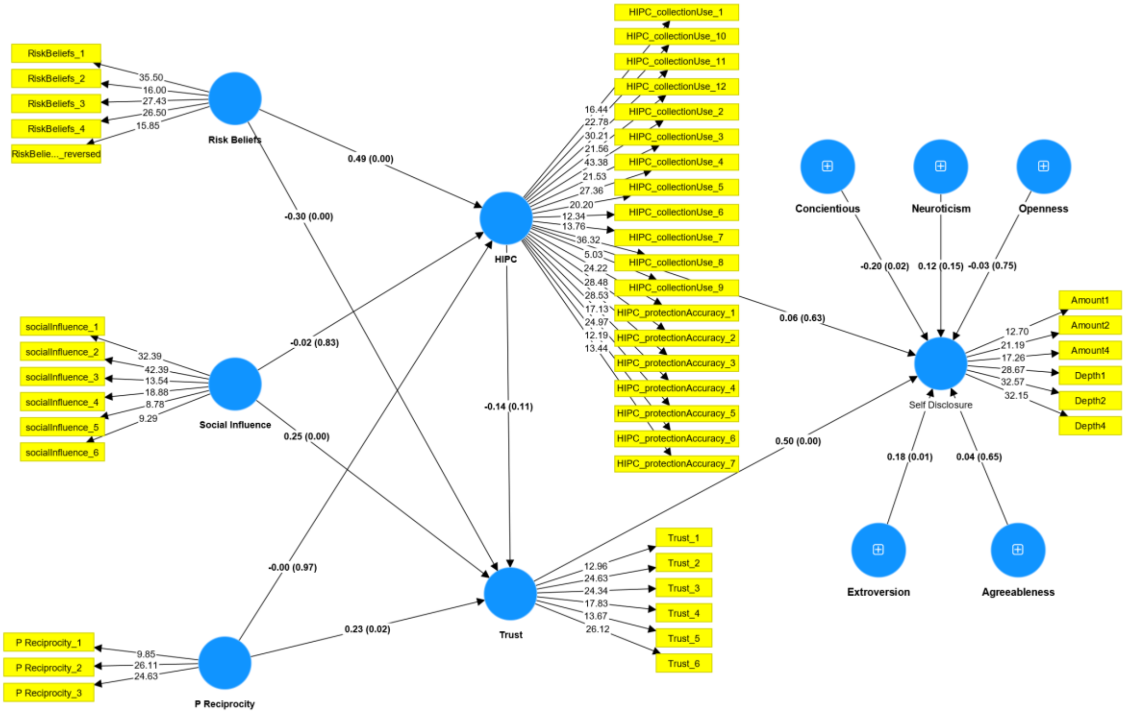


Figure 4.7 Structural Results: Females (n=141)

Construct	R^2
HIPC	0.25
THP	0.44
Self-Disclosure	0.28

Table 4.13 R^2 Results - Female

	Original Correlation	Correlation Permutation Mean	Permutation p-Values	Configural Invariance	Compositional Invariance
HIPC	1.000	0.999	0.704	Yes	Yes
P Reciprocity	0.996	0.997	0.272	Yes	Yes
Privacy Risk Beliefs	0.999	0.999	0.522	Yes	Yes
Self-Disclosure	1.000	0.999	0.748	Yes	Yes
Social Influence	0.999	0.998	0.588	Yes	Yes
THP	0.999	0.999	0.638	Yes	Yes

Table 4.14 MICOM Permutation test – by Gender

MICOM Result: partial measurement invariance stablished for all constructs (which allow path coefficients comparisons, the following MGA test)

	Path differences Gender(1.0) - Gender(2.0)	pvalues Gender(1.0) - Gender(2.0)	Sig
Agreeableness -> Self Disclosure	-0.057	0.604	
Conscientious -> Self Disclosure	0.099	0.421	
Extroversion -> Self Disclosure	-0.180	0.075	
HIPC -> Self Disclosure	0.068	0.642	

HIPC -> THP	-0.020	0.861	
Neuroticism -> Self Disclosure	0.012	0.910	
Openness -> Self Disclosure	-0.067	0.572	
P Reciprocity -> HIPC	0.110	0.422	
P Reciprocity -> THP	0.115	0.364	
Privacy Risk Beliefs -> HIPC	0.115	0.284	
Privacy Risk Beliefs -> THP	0.145	0.169	
Social Influence -> HIPC	-0.030	0.845	
Social Influence -> THP	0.072	0.572	
THP -> Self Disclosure	-0.010	0.920	

Table 4.15 MGA test - Comparing Path coefficients between Gender groups

The results of this analysis showed that no path differences existed between gender group and this finding was observed at 5% level of significance. In consequence, we cannot argue that any observed differences between gender groups in the models are relevant in statistical terms.

4.9.2 Post-Hoc Analyses

Further post hoc group comparison analyses were undertaken to determine whether differences existed in relation to occupation, age, education, level of internet experience, health status and illness sensitivity that are influencing the relationships under examination.

Occupation

Two groups were examined – those who were employed (including self-employed) and those who were students or not employed. In total 49.3% of respondents were employed or self-employed, 40% were students and 9.3% were homemakers or retired. As can be seen, compositional invariance was obtained for all constructs other than conscientiousness, social influence, and trust. The MGA test showed that the path from social influence to HIPC was significant at the 0.05% level, as was the path from trust to self-disclosure. However, as compositional invariance was not obtained for social influence or trust, we cannot be sure that this represents a real difference between the groups, or if it results from interpretational differences.

	Original correlation	Correlation permutation mean	Permutation p value	Configural Invariance	Compositional Invariance
Agreeableness	1.00	1.00	0.24	Yes	Yes
Conscientious	1.00	1.00	0.00	Yes	
Extroversion	1.00	1.00	0.40	Yes	Yes
HIPC	1.00	1.00	0.10	Yes	Yes
Neuroticism	1.00	1.00	0.54	Yes	Yes
Openness	1.00	1.00	0.26	Yes	Yes
P Reciprocity	1.00	0.99	0.61	Yes	Yes
Risk Beliefs	1.00	1.00	0.58	Yes	Yes
Self-Disclosure	1.00	1.00	0.06	Yes	Yes

Social Influence	0.99	1.00	0.03	Yes	
Trust	1.00	1.00	0.02	Yes	

Table 4.16 MICOM Permutation test – by Occupation

	Diff (Employed/ SelfEmp - Student)	p value	Sig (@5%)
Agreeableness -> Self Disclosure	-0.23	0.19	
Conscientious -> Self Disclosure	-0.08	0.58	
Extroversion -> Self Disclosure	-0.18	0.20	
HIPC -> Self Disclosure	0.06	0.76	
HIPC -> Trust	0.08	0.53	
Neuroticism -> Self Disclosure	-0.09	0.51	
Openness -> Self Disclosure	-0.13	0.42	
P Reciprocity -> HIPC	-0.21	0.13	
P Reciprocity -> Trust	-0.08	0.54	
Risk Beliefs -> HIPC	0.21	0.11	
Risk Beliefs -> Trust	-0.03	0.89	
Social Influence -> HIPC	0.40	0.01	Yes

Social Influence -> Trust	0.23	0.16	
Trust -> Self Disclosure	0.42	0.02	Yes

Table 4.17 MGA test - Comparing Path coefficients between Occupation groups

Age

Two age categories were examined – those aged 18-30 years and those aged 30-50 years. As shown in table X, the MICOM test showed that compositional invariance was obtained for all constructs others than conscientiousness and neuroticism. When the path coefficients were examined (MGA test), the path between perceived reciprocity and HIPC was found to be significant as was the path between social influence and HIPC. This indicates that both perceived reciprocity and social influence exert a greater influence on HIPC for younger respondents, than is the case for older respondents.

	Original correlation	Correlation permutation mean	Permutation p value	Configural Invariance	Compositional Invariance
Agreeableness	1.00	1.00	0.26	Yes	Yes
Conscientious	1.00	1.00	0.04	Yes	
Extroversion	1.00	1.00	0.15	Yes	Yes
HIPC	1.00	1.00	0.78	Yes	Yes
Neuroticism	1.00	1.00	0.00	Yes	

Openness	1.00	1.00	0.06	Yes	Yes
P Reciprocity	1.00	1.00	0.84	Yes	Yes
Risk Beliefs	1.00	1.00	0.65	Yes	Yes
Self-Disclosure	1.00	1.00	0.35	Yes	Yes
Social Influence	1.00	1.00	0.63	Yes	Yes
Trust	1.00	1.00	0.20	Yes	Yes

Table 4.18 MICOM Permutation test – by Age

	Difference (Age_18-30 - Age_30-50)	pvalue	Sig
Agreeableness -> Self Disclosure	0.16	0.21	
Conscientious -> Self Disclosure	0.09	0.48	
Extroversion -> Self Disclosure	0.16	0.17	
HIPC -> Self Disclosure	-0.01	0.95	
HIPC -> Trust	0.12	0.33	
Neuroticism -> Self Disclosure	-0.16	0.22	
Openness -> Self Disclosure	-0.06	0.66	
P Reciprocity -> HIPC	0.30	0.04	Yes
P Reciprocity -> Trust	-0.14	0.34	
Risk Beliefs -> HIPC	-0.14	0.27	

Risk Beliefs -> Trust	-0.01	0.97	
Social Influence -> HIPC	-0.49	0.00	Yes
Social Influence -> Trust	0.03	0.85	
Trust -> Self Disclosure	-0.24	0.06	

Table 4.19 MGA test - Comparing Path coefficients between Age groups

Education

Respondents who had an undergraduate degree were compared with those who had not pursued further education having completed secondary school. The MICOM test showed that compositional invariance was obtained for all constructs other than openness and trust. When path coefficients were compared between the two groups (MGA test) this showed that the path between HIPC and self-disclosure was significant, indicating that HIPC has a stronger influence on self-disclosure for those respondents with an undergraduate degree, than is the case for those without higher education levels.

The path between social influence and trust and the path between trust and self-disclosure was also significant. However, as compositional invariance was not obtained for trust, whether these latter two outcomes represent a difference between the groups on the basis of education cannot be determined with confidence.

	Original correlation	Correlation permutation mean	Permutation p value	Configural Invariance	Compositional Invariance
Agreeableness	1.00	1.00	0.18	Yes	Yes
Conscientious	1.00	1.00	0.11	Yes	Yes
Extroversion	1.00	1.00	0.14	Yes	Yes
HIPC	1.00	1.00	0.85	Yes	Yes
Neuroticism	1.00	1.00	0.11	Yes	Yes
Openness	1.00	1.00	0.00	Yes	
P Reciprocity	1.00	0.99	0.49	Yes	Yes
Risk Beliefs	1.00	1.00	0.90	Yes	Yes
Self Disclosure	1.00	1.00	0.78	Yes	Yes
Social Influence	0.99	0.99	0.53	Yes	Yes
Trust	0.99	1.00	0.00	Yes	

Table 4.20 MICOM Permutation test – by Education

	Difference (Undergrad - Secondary or less)	pvalue	Sig
Agreeableness -> Self Disclosure	-0.11	0.59	

Conscientious -> Self Disclosure	0.10	0.62	
Extroversion -> Self Disclosure	0.27	0.09	
HIPC -> Self Disclosure	0.75	0.01	Yes
HIPC -> Trust	0.17	0.31	
Neuroticism -> Self Disclosure	0.16	0.30	
Openness -> Self Disclosure	-0.30	0.08	
P Reciprocity -> HIPC	0.23	0.23	
P Reciprocity -> Trust	-0.04	0.80	
Risk Beliefs -> HIPC	-0.03	0.80	
Risk Beliefs -> Trust	-0.33	0.05	Yes
Social Influence -> HIPC	0.14	0.50	
Social Influence -> Trust	0.11	0.57	
Trust -> Self Disclosure	0.47	0.02	Yes

Table 4.21 MGA test - Comparing Path coefficients between Education groups

Level of Internet Experience

Respondents with more than 10 years internet experience (77.4%) were compared with those with less than 10 years internet experience (22.7%). The MICOM permutation test showed that compositional invariance was obtained for all constructs other than conscientiousness and neuroticism. When path coefficients of the two groups (MGA test) were compared, this showed that the path between HIPC and Trust was significant, indicating that HIPC exerts a stronger effect on trust beliefs for long term users of the Internet, than is the case for those with less Internet Experience. Similarly, the path between perceived reciprocity and trust was significant, indicating that perceived reciprocity exerts a stronger effect on trust beliefs for those with more than 10 years Internet experience, than is the case for those with less Internet Experience.

	Original correlation	Correlation permutation mean	Permutation p value	Configural Invariance	Compositional Invariance
Agreeableness	1.00	1.00	0.16	Yes	Yes
Conscientious	1.00	1.00	0.00	Yes	
Extroversion	1.00	1.00	0.26	Yes	Yes
HIPC	1.00	1.00	0.56	Yes	Yes
Neuroticism	1.00	1.00	0.00	Yes	
Openness	1.00	1.00	0.21	Yes	Yes
P Reciprocity	0.99	0.99	0.19	Yes	Yes
Risk Beliefs	1.00	1.00	0.56	Yes	Yes
Self Disclosure	1.00	1.00	0.54	Yes	Yes
Social Influence	1.00	1.00	0.67	Yes	Yes
Trust	1.00	1.00	0.64	Yes	Yes

Table 4.22 MICOM Permutation test – by Internet Experience

	Difference (long-term users - new users)	pvalue	Sig
Agreeableness -> Self Disclosure	-0.25	0.10	
Conscientious -> Self Disclosure	0.06	0.69	
Extroversion -> Self Disclosure	0.02	0.88	
HIPC -> Self Disclosure	-0.07	0.67	
HIPC -> Trust	-0.31	0.02	Yes
Neuroticism -> Self Disclosure	-0.01	0.94	
Openness -> Self Disclosure	0.00	0.98	
P Reciprocity -> HIPC	-0.33	0.12	
P Reciprocity -> Trust	-0.30	0.03	Yes
Risk Beliefs -> HIPC	0.20	0.36	
Risk Beliefs -> Trust	-0.07	0.57	
Social Influence -> HIPC	0.19	0.35	
Social Influence -> Trust	0.11	0.41	
Trust -> Self Disclosure	-0.05	0.72	

Table 4.23 MGA test - Comparing Path coefficients between Internet Experience groups

Health Status

A total of 20% of respondents reported having a chronic illness that impacted their lives. Those respondents with chronic illness were compared to those who did not have chronic illness. The MICOM permutation test showed that compositional invariance was obtained for all constructs. When the path coefficients between the two groups were compared, the MGA test showed marginal differences between the groups in relation to the path between openness and self-disclosure and trust and self-disclosure.

	Original correlation	Correlation permutation mean	Permutation p value	Configural Invariance	Compositional Invariance
Agreeableness	1.00	1.00	0.07	Yes	Yes
Concientious	1.00	1.00	0.31	Yes	Yes
Extroversion	1.00	1.00	0.23	Yes	Yes
HIPC	1.00	1.00	0.48	Yes	Yes
Neuroticism	1.00	1.00	0.19	Yes	Yes
Openness	1.00	1.00	0.55	Yes	Yes

P Reciprocity	1.00	0.99	0.53	Yes	Yes
Risk Beliefs	1.00	1.00	0.38	Yes	Yes
Self-Disclosure	1.00	1.00	0.55	Yes	Yes
Social Influence	1.00	1.00	0.55	Yes	Yes
Trust	1.00	1.00	0.89	Yes	Yes

Table 4.24 MICOM Permutation test – by Chronic Illness

	Difference (Cronic Illness_yes - Cronic Illness_no)	pvalue	Sig
Agreeableness -> Self Disclosure	0.01	0.94	
Conscientious -> Self Disclosure	-0.10	0.42	
Extroversion -> Self Disclosure	0.12	0.33	
HIPC -> Self Disclosure	0.12	0.39	
HIPC -> Trust	0.13	0.38	
Neuroticism -> Self Disclosure	0.03	0.84	
Openness -> Self Disclosure	0.22	0.10	Marginally
P Reciprocity -> HIPC	0.06	0.83	
P Reciprocity -> Trust	0.00	1.00	

Risk Beliefs -> HIPC	-0.03	0.89	
Risk Beliefs -> Trust	-0.02	0.83	
Social Influence -> HIPC	0.20	0.36	
Social Influence -> Trust	0.14	0.37	
Trust -> Self Disclosure	0.19	0.10	Marginally

Table 4.25 MGA test - Comparing Path coefficients between Chronic Illness groups

Sensitive Illness.

12% of respondents had reported having a sensitive illness. This group was compared to those respondents who did not have a sensitive illness to determine if differences existed between the two groups in relation to the relationships under examination. The MICOM test showed that compositional invariance was obtained for all constructs other than conscientiousness and openness. The MICOM permutation comparing the path coefficients between the two groups showed that the path between HIPC and self-disclosure was significant (indicating the greater influence of HIPC on self-disclosure for those with sensitive illness), as was the path between perceived reciprocity and Trust (indicating the greater influence of perceived reciprocity on trust beliefs for those with sensitive illness). Both the path between openness and self-disclosure and between social influence and HIPC were marginally significant.

	Original correlation	Correlation permutation mean	Permutation p value	Configural Invariance	Compositional Invariance
Agreeableness	1.00	1.00	0.26	Yes	Yes
Conscientious	1.00	1.00	0.02	Yes	
Extroversion	1.00	1.00	0.12	Yes	Yes
HIPC	1.00	1.00	0.17	Yes	Yes
Neuroticism	1.00	1.00	0.48	Yes	Yes
Openness	1.00	1.00	0.04	Yes	
P Reciprocity	0.99	0.99	0.16	Yes	Yes
Risk Beliefs	0.99	1.00	0.09	Yes	Yes
Self Disclosure	1.00	1.00	0.60	Yes	Yes
Social Influence	1.00	0.99	0.61	Yes	Yes
Trust	1.00	1.00	0.91	Yes	Yes

Table 4.26 MICOM Permutation test – by Sensitive Illness

	Difference (Sensitive Illness_yes - Sensitive Illness_No)	pvalue	Sig
Agreeableness -> Self Disclosure	-0.05	0.64	
Conscientious -> Self Disclosure	0.02	0.89	
Extroversion -> Self Disclosure	0.16	0.32	
HIPC -> Self Disclosure	0.53	0.01	Yes
HIPC -> Trust	0.10	0.46	
Neuroticism -> Self Disclosure	0.19	0.21	
Openness -> Self Disclosure	-0.27	0.10	Marginally
P Reciprocity -> HIPC	-0.36	0.15	
P Reciprocity -> Trust	0.30	0.05	Yes
Risk Beliefs -> HIPC	-0.02	0.87	
Risk Beliefs -> Trust	-0.10	0.52	
Social Influence -> HIPC	0.59	0.09	Marginally
Social Influence -> Trust	-0.03	0.80	
Trust -> Self Disclosure	0.09	0.53	

Table 4.27 MGA test - Comparing Path coefficients between Sensitive Illness groups

4.10 Chapter Summary

The results show that all the factors in the model were reliable, the metrics of the model indicating a good fit, and a sufficient sample size was selected from this study. The U.S and Irish models demonstrated positive relationships between privacy risk beliefs and HIPC, between perceived reciprocity and trust in online health platforms, and between trust in online health platforms and self-disclosure. Significant negative relationships between privacy risk beliefs and trust in online health platforms and between HIPC and trust in online health platforms were also found in both models. The U.S. model found H8, H11, and H13 to be significant, whereas the Irish model found H14 to be significant.

The validation of the structural model demonstrated satisfactory results. The R^2 were substantial, with moderate to satisfactory values. Of note The R^2 for the U.S. model and Irish model for self-disclosure were 0.46 and 0.15, respectively.

The path differences between the models included social influence to trust in online health platforms, conscientiousness to self-disclosure, privacy risk beliefs to health information privacy concerns, and trust in online health platforms to self-disclosure. All constructs showed partial measurement invariance except for perceived reciprocity.

5 Chapter Five: Qualitative Analysis

5.1 Introduction

This chapter explores the qualitative analysis of interviews collected from Irish and U.S. users. The purpose of collecting qualitative data is firstly to gain a deeper understanding of the constructs presented in the research framework, and secondly to explore the relationships between the constructs and online self-disclosure in a health context. The chapter outlines the qualitative analysis procedures, provides a description of the sample, and an overview of data validation procedures. The chapter then discusses the main findings from qualitative analysis, first from an Irish perspective and then from a U.S. perspective. Finally, quantitative and qualitative data are integrated to provide a holistic view of user self-disclosure of health information in both Ireland and the U.S.

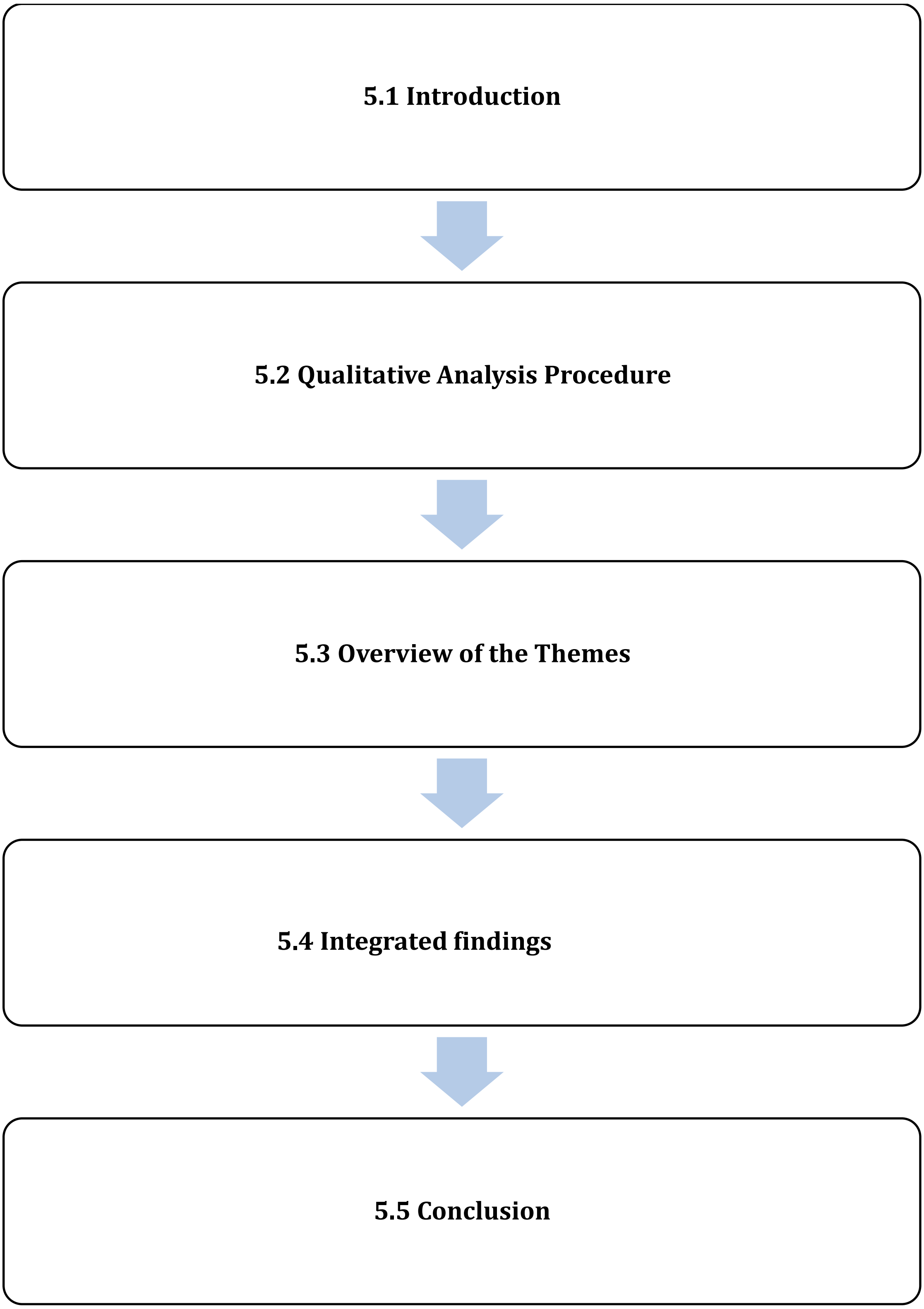


Figure 5.1 Chapter Structure

5.2 Qualitative Analysis Procedure

A Framework analysis approach (Ritchie and Spencer, 1994) was used for this study. Framework analysis is a deductive analysis technique that has been used in both health research and IS research (Gale *et al.*, 2013; Fox and Connolly, 2018). This technique is more accessible than some competing techniques as it does not require detailed technological knowledge (Gale *et al.*, 2013), moreover it is useful when constructs have already been identified (Ritchie and Lewis, 2003) such as the present study. A key feature of framework analysis is that it allows the researcher to reduce data through summarisations and synthesis while retaining links to the original data (Ritchie and Spencer, 1994; Gale *et al.*, 2013).

For this study an interview guide was used that included all key constructs drawn from the research framework. Following best practices outlined by Ritchie and Lewis, (2003) each interview was transcribed verbatim and listened back to a number of times for errors and also to note any verbal or tonal moments of significance. Following this a staged process outlined by Ritchie and Spencer, (1994) and Gale *et al.*, (2013) was adhered to:

1. Familiarization with the Data: This is the first step in the process, transcripts are created, read, and re-read. During this phase, notes are taken of potential codes or themes that may be interesting or important.

2. Generating Initial Codes: After familiarising the data, initial codes are produced from the data. Coding is the process of segmenting and labelling text to identify statements that are of interest or seem to be relevant to the research question. For example, a segment of text could be coded as "privacy concerns" if a participant expresses worry about their personal data being mishandled.

3. Searching for Themes: After coding the entire dataset, themes are sought amongst the codes. This involves sorting the different codes into potential themes and collating all the relevant coded data extracts within the identified themes. For instance, codes like "errors," "trust in platform," and "improper access" could be grouped into a larger theme like "Privacy Concern."

4. Reviewing Themes: This phase involves refining the identified themes upon review of the themes against the dataset to ensure they accurately represent the data. Some themes can be discarded, combined, or subdivided during this phase.

5. Defining and Naming Themes: This involves identifying the "essence" of what each theme is about and determining what aspect of the data each theme captures.

6. Writing up: The final phase of thematic analysis is to tie it all together. A detailed analysis of each theme is provided, supported by extract examples, and connecting the analysis back to the research question and literature, presenting a coherent and persuasive account of the data.

Initially, each interview was listened back to a number of times alongside print outs of their transcripts. Notes were made in the margins of each transcript about each construct after which the data was reorganised in line with the constructs. Analytic memos were written up on each interview followed by a matrix consisting of indexed themes, codes and summarisations for each construct. All work was done with pen and paper and laid out on large A3 sheets in an effort to make the charting and interpretation process easier. When all indexed text was aligned with the appropriate construct, tables were then developed. Finally, these tables were used to find key links between the constructs in accordance with the research framework. Key findings were than written up as summarisations that can be linked back to the original data.

An example of the analysis is outlined in the table 5.1 below. The table represents the construct reciprocity along with initial broad codes and subsequent sub-codes followed by a note on the link to THP and HIPC.

Transcript extract	“I suppose it's fair, you know modern science has allowed me to be sitting here talking to you without any issues. Something which couldn't be done a decade and a half ago in Ireland. What happens to someone like me was in the past I was told they would just let your heart grow so big until it couldn't function anymore and then they give you an artificial valve. So that’s progress. So as a kind of a fairness thing. I feel it's very fair for me to contribute back to further research by being a walking research subject. But I don't feel any pressure because some random person sticks up something about what I have. If you know what I mean.”		
Theme/Construct	Reciprocity		
Codes	Trust “So that’s progress”	Concerns “let your heart grow so big until it couldn't function anymore”	
Sub-Codes	Expectation “I feel it's very fair for me to contribute back to further research”	Others “I don't feel any pressure because some random person sticks up something about what I have”	Fairness “I suppose it's fair”
Link to THP & HIPC	Reciprocity is influenced by the scenario. Privacy concern is not present		

Table 5.1 Coding example

5.2.1 Sample Overview

Due to the personal nature of this research all interviews were recorded, transcribed and analysed anonymously. As advised by O’Cathain *et al.*, (2014) only the characteristics of the participants are outlined. A total of 20 interviews were conducted (10 American and 10 Irish).

American interviews were made up of females (n=5) and males (n=5). Two age groups were represented, 18-24 (n=3) and 25-49 (n=7). All participants had an undergraduate degree (n=10), some also had a postgrad qualification (n=7). Participants were students (n=3) and employed in industries such as health (n=2) and technology (n=5).

Irish interviews were made up of females (n=3) and males (n=7). Three age groups were represented, 18-24 (n=4), 25-49 (n=4) and 50+ (n=2). All participants had a postgrad qualification or were in the process of completing one (n=10). Participants were employed in industries such as health (n=3) and technology (n=4) and retail (n=3).

5.2.2 Validation

While there is no one agreed upon approach for achieving validity in qualitative analysis a number of researchers have maintained that trustworthiness and validity can be achieved by using a structured process and reporting on the steps taken in the process (Teddlie and Tashakkori, 2009; Gale *et al.*, 2013; Venkatesh, Brown and Sullivan, 2016; Nowell *et al.*, 2017). As such this study has followed guidelines set out by Venkatesh, Brown and Sullivan, (2016) because they have been previously used in mixed methods research, health research and IS research. Venkatesh, Brown and Sullivan, (2016) describe three validation stages: 1) design validity, 2) analytical validity, and 3) inferential validity. Each of these will now be discussed.

Design validity is comprised of three sub sections: descriptive validity, credibility and transferability (Venkatesh, Brown and Bala, 2013). Descriptive validity refers to whether the data collected is representative of the participants' views, experiences and behaviours. To achieve this the researcher used follow up questions during the interviews in order to create fuller pictures of participants' experiences and observations. When transcribing, each interview was played back a number of times to note any vocal or tonal moments of importance. This step was repeated alongside print outs of the final transcripts. To achieve credibility, the researcher asked probing questions when participants gave ambiguous or conflicting statements. Some questions were asked in different ways to establish clarity and when clashing statements or misunderstandings were found member checking (Lincoln and Guba, 1985) was conducted, that is to say participants were asked if the researcher's understanding of a statement was accurate. Transferability, which deals with whether findings can be generalised is often a difficult task when dealing with qualitative data (Seale, 2018). In an effort to account for this the present study gathered data on the same phenomenon from two different countries and across a diverse group of participants, as per Venkatesh, Brown and Bala, (2013).

Analytical validity addresses how the data was collected and analysed so that the findings hold theoretical validity and are dependable, consistent and plausible (Venkatesh, Brown and Bala, 2013). Theoretical validity requires that links between hypothesised relationships and constructs are credible. This study has leveraged previously used theories and constructs and bridged them into a new research context. This has been achieved by extensive consultation with literature and the researcher's supervisor. Further theoretical validity is achieved by integration of findings from two different data types, in doing so the theoretical validity and credibility are strengthened (Bell, Bryman and Harley, 2018).

Dependability and consistency have been achieved by performing checks prior the collection of data. The research interview guide was checked and piloted amongst research peers in DCU and ASU. Any recommendations were then incorporated into the instrument. Plausibility of findings was achieved by reviewing final conclusions and summaries and comparing them with the literature for corroboration with previous findings and also with the overall participant outlooks.

Inferential validity consists of interpretive validity and confirmability (Venkatesh, Brown and Bala, 2013). In doing so it addresses the accuracy of the researcher's inferences. To achieve this a number of steps were taken. Data was collected by multiple methods to justify inferences, feedback from participants was sought during interviews by way of member checking and cross checking of coding was performed in order to strengthen findings. These findings are now presented with confidence in their validity and trustworthiness.

5.3 Overview of the Themes

The literature review and research framework presented a number of antecedents to online self-disclosure in a health context. Here each of the antecedents and themes are discussed individually.

5.3.1 Antecedents of THP, HIPC and Self-Disclosure (Ireland vs. US.)

5.3.2 Ireland - Reciprocity

The interviews aimed to gain an understanding of participants' feelings about reciprocity. Specifically, participants discussed whether reciprocity influenced their THP and whether it influenced their HIPC. During the interviews participants discussed reciprocity from the perspective of others' expectations of them to reciprocate interactions and sharing of personal health data, whether others trust them to reciprocate sharing and interaction, and whether it is only fair that users reciprocate sharing and interaction on digital health platforms (DHPs).

Overall participants displayed mixed feelings towards the role of reciprocity in the disclosures of personal health data. While some participants displayed no desire nor expectation to reciprocate the sharing of personal health information, others simply do not feel a compulsion to reciprocate the sharing of personal health information. Where only a very small amount of participants felt an obligation to reciprocate more were inclined to employ a case by case process. Two participants alluded that reciprocation of personal health information was only necessary in the case of targeted medical research projects. Others noted that without sharing of personal health information many DHPs would not exist.

5.3.2.1 Expectation belief

Many participants in this study displayed little to no obligation to reciprocate sharing of personal health data. In fact, many saw a benefit to the anonymous nature of a computer mediated environment.

"…maybe there's something about the anonymity of the internet. I can take something from a website or an app and see other people's contributions. I see people who have been on health websites where they have discussed their symptoms."

P1, Counsellor, Ireland

Others were more abrupt when discussing the expectation of reciprocation,

"I don't know and I don't care. That's being honest."

P3, Academic, Ireland

Conversely, some participants expressed a more subjective outlook, claiming one's attitude to reciprocation could be assessed on a case by case basis, *"I think it's kind of each to their own" (p2, Ireland).* In a similar vein one participant made reference to personality types,

"It depends on your personality, like I wouldn't be the type of person if I write something I'm going to expect someone else to add to it, but other people are."

P8, Masters student, Ireland

Other participants exhibited stronger expectation beliefs. Of note, these participants were more likely to refer to social sharing of health data as opposed to sharing of health data for research purposes. In particular Fitbit and liking of public posts was referred to in this instance, *"I think it's kind of an unwritten rule that if someone likes your post you've got to make sure you like their next one" (p7, Ireland).*

5.3.2.2 Trusting expectations of others

Participants attitude towards trusting expectations was similar to expectation belief. The majority of participants did not believe that others would trust them to reciprocate experiences and personal health information. Others were unsure and reverted to a case by case outlook. A few participants believed that others trusted them to reciprocate but only in specific scenarios such as when the online community is known to them, as can be seen in the following quote,

"The kind of relationship tends to be a bit different. Most of what I tweet is about health policy so a lot of the people I'm engaging with on Twitter are people into Irish, British or European health policy. And we all know each other. Well most of us know each

other in real life because we all attend the same conferences. So it's a slightly different animal."

P4, Public Health Professional, Ireland.

Echoing this sentiment that the environment played a decisive factor in the likelihood to reciprocate one participant stated "*I would say yes if it's more a closed forum, but a public one, no" (p8, Ireland).*

Some participants considered it a matter of personality as expressed in the following quote,

"…it's up to you like if I write something online I want it there. It's my opinion I wouldn't really think of some other person doing the same for me, it would just be up to me whether I want to post it or not."

P9, Masters student, Ireland

5.3.2.3 Fairness

The vast majority of participants did not believe it to be only fair that they should reciprocate and disclose personal health information on DHPs if other people do. Many believed there was no expectation of fairness, that there was no social contact or agreement. Others however believed that in specific scenarios it would be only fair to reciprocate and disclose personal health information. One participant noted that it was fair as without reciprocation and disclosures of personal health information many health platforms would not exist, *"there wouldn't be a platform if people weren't sharing" (p7, Ireland).*

A number of participants referred to context specific fairness in reciprocation, such as the following example, where sharing of personal health information has benefitted the participant, *“I suppose it's fair, you know modern science has allowed me to be sitting here talking to you without any issues. Something which couldn't be done a decade and a half ago in Ireland. What happens to someone like me was in the past I was told they would just let your heart grow so big until it couldn't function anymore and then they give you an artificial valve. So that’s progress. So as a kind of a fairness thing. I feel it's very fair for me to contribute back to further research by being a walking research subject. But I don't feel any pressure because some random person sticks up something about what I have.”*

P3, Academic, Ireland.

Of note, one participant did not consider their disclosures as an act of reciprocity but rather a step toward fulfilling a goal, something necessary but not instigated by fair and trustworthy considerations,

“...in a way the reason for producing the information is to effectively establish that we both have skin in the game.”

P4, Public Health Professional, Ireland

5.3.2.4 Review of reciprocity

Historically, reciprocation of experience can give rise to trust and information exchange. When greater reciprocation occurs trust is developed and in turn deeper disclosures are often made. In a computer mediated environment it does not appear as though the same expectation of reciprocity exists.

A number of factors appear to encourage or discourage reciprocal sharing of personal health information on a case to case basis; personality, public versus private platforms, anonymity, purpose of the data (medical research/ fitness data for social media) and familiarity of community. Of note, at no point did any participant refer to privacy concerns when considering to reciprocate the disclosure of personal health information. Some participants referred to trusted communities helping to facilitate greater levels of reciprocation and disclosures.

- **Summary point: The link between trust and reciprocity in the given context is present among some participants. Participants indicated that levels of reciprocity can grow and are dependent on a number of subjective factors relating to personality, platform and purpose. Participants indicate that when online communities are trusted and familiar, reciprocity appears more likely to occur. Participants did not indicate that privacy concerns influence reciprocity.**

5.3.3 Ireland - Social Influence

The interviews aimed to gain an understanding of participants' feelings towards social influence and its role in trust development and impact on HIPC. Specifically, participants discussed whether encouragement from those close to them influenced their trust and self-disclosures, if the benefits others share influences them, if health professionals' encouragement plays an influential role and if social influence had any role in their HIPC.

5.3.3.1 Encouragement from Close Friends or Family

Almost every participant could refer to a personal anecdote of friends or family members encouraging them to use or consider using a health platform. In most cases this encouragement was due to perceived and observed health and fitness benefits on the part of the family member or close friend. In some cases, the encouragement was born of a concern for a loved one's health. The below quote relates to a participant and his wife hearing of the death of a neighbour and the ensuing take up of a health platform to monitor cardiac health.

"I found out an old neighbour of mine, her husband passed away with the same condition I had. When she (wife of participant) heard about this she was shocked. And you know, yeah, she obviously encourages it. "

P3, Academic, Ireland

Many participants had friends encourage them to use health platforms, "*I wouldn't have known anything about it unless my friend who uses it told me", (p1, Ireland).* A number of other participants noted the general knowledgeability of their friends or family playing a role in their adoption of health platforms, as observed in the following quote.

"Most of the people I hang out with are people well aware of the technologies coming up in the markets. If somebody mentioned something and if they sell it to me like if it sounds interesting I would actually go and pick it up or try it out just to see how it works."

P6, Masters student, Ireland

5.3.3.2 The Benefits of Others

Similar to encouragement from those close to them, almost every participant signalled that those around them garner benefit from health platforms and as such this has positively impacted their adoption of health platforms. The benefits perceived and obtained varied but the majority of participants listed routine monitoring of healthy habits such as exercise, regular heartbeat and diet. Others referred to benefits beyond tracking of fitness data, to preservation of a good health status. Some participants noted that their families share data and useful health information through these health platforms. The widespread use of Fitbits and fitness platforms was evident in almost every interview as exhibited below.

"Yes, there are people around me using apps, and I know lots of people using Fitbit. Some people really you know live by them."

P3, Academic, Ireland

Interestingly, one participant postulated a reason for such an uptake in health platforms mainly that some adoption of health platforms can be accounted for via a cultural and generational observation of their perceived benefits, as outlined in the below comment.

"Yeah quite a lot of people do. I think that it seems to be something that's quite compatible with millennials. There seems to be a cultural move towards trying to optimize our lives, our performance, our health, our wellness."

P1, Counsellor, Ireland

Others made reference to the benefits in tracking one's health and fitness progress. Indeed, when this tracking was shared with family members or friends further benefit was perceived as a result of gamification.

"I think there's a gamification aspect to it. You want to beat your friends. My Dad is the same, he used to be a very good runner when he was young. But gave it up and put on a few pounds and now he's lost everything he's been training a few groups now. I think it all pretty much stems from Garmin and being able to see your progress"

P7, Masters student Ireland.

Another participant referenced that those around them gain benefits from using health platforms but also claimed that people are aware of the benefits of such platforms while having little knowledge of the dangers perceived with sharing personal health information, *"I don't think they're knowledgeable to the impact of them putting their information out there if someone was to access it", (p10, Ireland).*

5.3.3.3 Status Symbol

The greater majority of participants believed that the sharing of health data on certain platforms could contribute to a symbol of status. Almost all agreed that deriving status from the sharing of health information pertained to social media platforms such as Instagram, as exhibited in the following quote.

"Absolutely I mean if you just look at Instagram I mean all these fitness pages, I know it's not a fitness platform but I think that people have made it to where their accounts are just about health and fitness. It's an absolute status symbol."

P2, Masters student, Ireland

Others noted it as a phenomenon but took a personal outlook on the matter, "*it wouldn't appeal to me personally" (p3, Ireland).* Echoing this scenario specific outlook some participants believed that a symbol of status could be achieved within particular communities, one participant referring to the athletics community noted, "*if they run a good time for a race they'll post it and they'll get lots of congratulations" (p7, Ireland).*

A small number of participants believed that the sharing of health and fitness information was less about gaining status and more about motivating themselves.

5.3.3.4 Encouragement from Health Professionals

Every participant expressed that if a health professional encouraged them to adopt a health platform they would indeed consider it. All participants said they would happily consider a suggestion from a health professional, one participant indicated that they already have taken on such a suggestion.

5.3.3.5 Review of Social Influence

The role of social influence as it relates to THP is clear and evident. Almost every participant could recall a friend or family member encouraging them to use a health platform and as such the vast majority of participants took up the use of a health platform or device. In many cases this take up translated into regular sharing of health data and useful health information amongst trusted communities. Further to this all participants indicated that should a health professional encourage the use of a health platform they would consider this suggestion.

With regard to the benefits others gain from health platforms, again almost all participants had experience of those close them gaining benefits. These benefits ranged from daily health and fitness improvements to quality of life and cardiac health improvements. Others listed gamification, tracking and information sharing as possible benefits. It was noted that while the perceived benefits were well identified the same could not be said for perceived dangers or risks.

Finally, almost all participants believed that the usage of health platforms could facilitate the development of one's status. Notably, any status symbol development might be enhanced with disclosure of health and fitness data to more traditional social media platforms. It would also appear that disclosure of health and fitness data in trusted communities and targeted platforms can contribute the status development. No participant referred to social influences having an impact on HIPC, positive or negative.

- **Summary point: the link between social influence and THP is clear and evident among participants. According to participants health professionals, family and close friends can heavily influence one's likelihood use a health platform and to therefore disclose personal health information within trusted communities. Participants have observed health and fitness benefits indicate that this can positively influences one's likelihood use a health platform. According to participant's status can be achieved by disclosing health information in both open and closed digital communities. Participants made no reference to social influence having any impact on HIPC.**

5.3.4 Ireland - Privacy Risk Belief

The interviews aimed to gain an understanding of participants' privacy risk beliefs and their influence on THP and HIPC. Specifically, participants discussed their perception of risk when sharing information online, if they believed there to be potential for loss when sharing information online, and finally if they feel safe when sharing information online.

Every participant acknowledged that there is an inherent risk sharing information online, moreover every participant agreed there to be a potential for loss when disclosing information online, though the risk and potential varied. Almost every participant expressed not feeling safe when sharing information online however this feeling varied in degree from person to person. The following sections will look at these three components individually.

5.3.4.1 Perception of Risk

All participants agreed that there is risk involved with sharing personal information online. While the vast majority believed this risk to be inherent and somewhat inevitable, *"Yes you never know who you are sharing it with, you never know what it's going to be used for in broader terms", (p8, Ireland).* Others believed risk to exist but that it is avoidable if one is aware of potential risks, *"no, once you're aware of the risk", (p3, Ireland).* Indeed, participants on the whole displayed an awareness of risk to privacy online as evidenced in the following comment.

"I mean the biggest risk is probably identity theft and data aggregation. Now here we have fairly strong laws here against data aggregation. So you require permission to process other people's data even when it's available online in almost any way shape or form whereas in the US it's a big business aggregating data and it's intrusive. There

are websites in the states where you can type in someone's name and you get swathes of information from public sources about them. Here to create such a website would be data processing and it would be illegal."

P4, Public Health Professional, Ireland

5.3.4.2 Potential for Loss

All participants referred to the potential for loss when sharing information online however the degree of loss and general concern about loss of data varied considerably. The majority of participants referred to identity theft when discussing potential loss but also to the potential to avoid loss with the correct understanding of security features, *""I think it's a risk with identity theft and you know the problem I suppose is that for most, people don't understand the issues", (p4, Ireland).* Others however while acknowledging the potential for loss simply did not care and did not believe any loss could have a negative impact on them, *"someone could just hack in and read everything I believe, but I don't think that my health information is so interesting that anyone would want to read it and then so what if they can read it, I don't see what they could do with it", (p2, Ireland).*

Some participants referred to less harmful forms of loss such as being subjected to spam or targeted advising, while one participant noted that there are benefits to weigh against the potential for loss*, "Yes, I think there is, but in saying that I think there's high potential for gain as well, like the data that they do collect, if it's metadata it's all compiled it can show trends and maybe improve medicine", (p7, Ireland).*

The overriding outlook was one of potential loss but that it is avoidable if individuals take responsibility for themselves and their actions as expressed in the following statement.

"I'm constantly called back to Einstein you know. His famous saying there's two things without end. One is the universe and the other is humans' stupidity. In my time I have seen so many people doing so many stupid things it's unbelievable. But as an accountant as an academic and a business owner I just think how can you be so stupid? You know? You know you get an email from paypal.tr.jp. whatever and they ask you for your passwords and you're dumb enough to give it to them. I don't want to be mean but maybe it's a lack of education."

P3, Academic, Ireland

5.3.4.3 Safe Online

The majority of participants referred to not always feeling safe when disclosing information online however this admittance seems to have had little to no impact at all as to their tendency to disclose information online, *"no, I do it, but it's not safe", (p9, Ireland).* Others claimed to disclose in a secure manner while still being aware of potential dangers, "*I always think about it carefully, but I do share", (p4, Ireland).* Some participants felt safe when sharing online but only in scenario specific contexts. Interestingly one participants noted that while they acknowledged a lack of safety online they disclosed information anyway as they had become so accustomed to it.

"Maybe I've used the Internet so often and frequent these sites it's almost like don't really think about it. Like crossing the road like. I don't feel safe in the middle of the road. but I do it so often."

P1, Counsellor, Ireland.

5.3.4.4 Review of Privacy Risk Belief

It is evident that all participants believe there is a risk when one discloses information online. While some participants feel this risk is somewhat inevitable others displayed strong beliefs that risk is only truly present when considered against individual competence and care. As to the nature of the risks almost all believed identity theft to be a clear and obvious danger while lesser risk exits such as targeted marketing campaigns. The benefits to information disclosure were also recognised. Finally, almost all participants agreed to feeling unsafe at times when disclosing information online but for almost all this feeling was scenario specific. This lack of safety did little to deter disclosures of information.

- **Summary point: while privacy risks are acknowledged by participants they do little to deter trusting behaviours. Participants indicated that risk beliefs can play a low role in their HIPC. According to participant's risk is considered directly proportional to an individual's online safety competence.**

5.3.5 Ireland - Health Information Privacy Concerns

The interviews aimed to develop an understanding of users' health information privacy concerns, how they impact THP and consequently self-disclosure. All participants expressed a concern for privacy as it relates to health data. The level of concern varied on a case by case context and for some participants' concern pertained only to the future as data collection habits increase. Each dimension of HIPC will now be discussed in this section.

5.3.5.1 Collection

Collection refers to the frequent and large collection of health data that is stored digitally. Almost every participant expressed unease with vast amounts of health data being stored, though almost all also agreed that there can be targeted research benefits to such actions when undertaken by the correct bodies as expressed in the following statement, *"I think it should be done and should be encouraged", (p3, Ireland).* Most participants believed that only public health bodies should have access to such large datasets, fearing unwanted targeted advertising from private entities. While some others saw the benefits of such collection and storage but also worried that it could contribute to a *"surveillance society", (p1, Ireland).* The following quote represents the common view that collection and storage has benefits, but that there should be conditions attached to such collection and storage

> *"I think there's a couple of things needed. One is a fairly high level of security which is difficult to achieve but it can be achieved. The other is appropriate and effective regulation. And I think we are probably at the point where you know the next company that is discovered to have an unsecured device instance with all its clients details on it will be fined so much money in Europe that they will close."*
>
> *P4, Public Health Professional*

- **Summary point: participants express concern for collection and storage of personal health information. They do however recognise the possibility for medical and research benefits. They express distrust of private companies' collection and storage of personal health information. Participants continue to disclose health information despite HIPCs. Participants want personal health information to be strongly secured and regulated.**

5.3.5.2 Unauthorised Secondary Use

Unauthorised secondary use refers to user's concern that health data might be used for secondary purposes. Almost every participant expressed a concern for unauthorised secondary use of their personal health data. The most common concern was for targeted health advertisements from private companies, as expressed in the following example.

"They want you to try a different kind of medicine. I really think they're trying to push something else onto me based on my diagnosis. That's the kind of thing I don't like."

P6, Masters student, Ireland

Participants agreed that there are benefits to secondary use but that any benefit should be derived from public or governmental bodies due to a lack of trust in private entities, "*it should be used but it should be used under very severe restrictions and I'm firmly of the view that it should not be made available to the private sector under any circumstances or for any reason because I don't trust them", (p4, Ireland).* In addition to this view many participants believed that they should have the ability to decide what entities can gain access to their personal health information, moreover all agreed that data should be anonymised.

- **Summary point: participants displayed concern for secondary use. Participants did however appreciate that there are medical and research benefits to secondary use of personal health data. Participants distrust private industry access to health data. Any secondary use should be restricted, anonymised and used by public entities only.**

5.3.5.3 Improper access

Improper access refers to user's concern that their health data might be accessed by unauthorised parties. While all participants expressed concern as to improper access the nature of this concern varied greatly. Many expressed concern for unwanted access to their health data, be it from individuals or private entities, but freely admitted that this concern was due to a lack of understanding about the protections around their data and how it can be a processed, *"I do worry about that because I really don't know what the checks are.", (p6, Ireland).* Some others expressed a concern for improper access based on having an awareness of publicised incidents.

In contrast to this a small number of participants had little regard for concerns relating to improper access depending on who had the access and what manner of data was in question. For example, one participant believed there is little to be concerned about so long as anonymised meta data was in question and that employers had no access to said data. Health services or insurance entities on the other hand were deemed suitable for having free access to meta data en masse.

> *"Employers I would say no. Insurance companies possibly but it has to be anonymised. So that they could have access to the rate, the increase in heart attacks in Ireland for example. That kind of stuff but not personally identifiable data."*
>
> *P3, Academic, Ireland*

Summary point: participants express concern relating to improper access but this concern is medium to low and dependent on the nature of the data and the purpose of its use.

5.3.5.4 Errors

Error relates to users' concern as to the possibility of errors in their health data. Participants expressed a concern for errors in their personal health data but similar to other HIPC dimensions this concern varied from strong concern to minimal concern. Those most concerned with errors were both dependant on medical devices and working or studying in healthcare. Concerns varied from being prescribed the wrong medication to a device not accurately monitoring their physiological conditions. Of note many expressed positive outcomes from digital health tools, such as reduction in error and the elimination of double transcriptions in decision support systems. None the less a combination of human error with support system errors was noted, as evidenced in the following example.

> *"And if you remember the Savita case, she was a young woman who came into hospital, on admission, she had signs of significant sepsis nothing was done about it. Tests were taken which showed that she almost certainly had significant sepsis and they were missed. She would probably have survived. Had she been given large amounts of I.V. antibiotics on admission. People screwed up. And decision support tools don't stop that. But they do make it less likely."*
>
> *P4, Public Health Professional, Ireland*

Some other participants acknowledged the risks associated with errors in health data but didn't see it as something to concern them on a personal level, but that maybe it could in the future. While others recognised that there will always be errors but that the more important factor was measuring trends, *"Performance* *measures don't need to be accurate sometimes they can never be, its's the trends that are more important.", (p3, Ireland).*

Summary point: participants expressed concern for errors in health data but the level of concern varied depending on personal background and individual reliance on accurate health records.

5.3.5.5 Control

Control refers to users' belief or lack thereof that they have control over their health data. Almost all participants claimed a lack of control over their own personal health data. Of those who expressed a lack of control their desire was almost unanimously for to have total control as detailed in the following, *"My view is that you should own your own health data, other people have rights of access to it but they should be subject to your control" (p4, Ireland).* Others expressed a lack of control over personal health data while admitting having little to no knowledge about what control systems might exist.

In contrast, a small number of participants showed little regard for control concerns insofar as they are willing and happy to trust in technology to protect their control. This outlook is best summarised in the below statement.

> *"In terms of my own stuff? I'm happy enough. My line on an iPhone is if you want to see what's on there you need my finger so you're going to have to cut my effin finger off if you want to get in. I know stuff is stored in the cloud. I've seen cloud centres that to me sometimes are way more secure than they even need to be so I'm happy with that. How many cases have we heard of HSE files found in bins? If its electronic and used properly I'm confident about it. If it's paper. I'm not saying I'd worry; I'd be more dubious."*
>
> *P4, Academic, Ireland*

- **Summary point: participants feel they have a lack of control over their health data. They would like greater control over who can see and use their health data. A small number of participants feel they have adequate control.**

5.3.5.6 Awareness

Awareness refers to user's awareness of how their personal health information is used and protected. Most participants claimed to have "*no idea", (p2, Ireland),* as to how their personal health information is used and protected. Indeed, their lack of awareness is evidenced by their almost uniform inability to elaborate on the topic. The most common response being, *"I think we should be more aware. I should be more aware of it.", (p6, Ireland).* While this lack of awareness was almost uniform one participant's response only strengthened this finding as noted below.

> *"There was a survey done I think three years ago and that they asked people what they thought about what was being done with the health data. Most people thought that all their health data was shared across the health service already. Which it isn't. It should be. I would argue very strongly and one of my colleagues in HSE has devised a technique actually based on blockchain for recording consent to sharing data which could be implemented in the morning. It's certainly technologically feasible to do that now which it maybe wasn't 10 years ago, recording consent has always been a bit of the Achilles heel."*
>
> *P4, Public Health Professional, Ireland*

While participants displayed both a lack of awareness of how their personal health information is used and protected and also a concern for the implications associated with improper use of health data, it should be noted that all participants previously acknowledged freely sharing personal health information.

- **Summary point: participants appear to have almost no awareness as to how their personal health information is used and protected. This however has done little to impact their likelihood to disclose personal health information. Participants did display a strong desire to have greater knowledge and control over how their personal health information is used and protected.**

5.3.5.7 Review of HIPC

Every participant expressed concern for their personal health information however, the level of concern varied. Almost all participants claimed to distrust private companies having access to their personal health data but the concern was lower in those who had acute dependencies on health technologies.

All participants claimed to have concern for how their data was collected, stored, used and control. Only those with acute dependencies on health technologies expressed high levels of concern for errors in heath data. These concerns did nothing to change their information sharing behaviours. In addition, every participant, expect for two, claimed to have little to no knowledge as to how their personal health data is stored and used. The combination of concern for privacy, expressed distrust of health technology vendors and continued health disclosure behaviour raises the question of the privacy paradox being present in these findings.

- **Summary point: participants all express concern for their health data and a lack of trust in health technology vendors yet they all appear to continue to self –disclose health information. Participants appear to have almost no awareness as to how their personal health information**

is used and protected. Participants expressed concern for errors in health data but the level of concern varied depending on individual digital competencies. Participants express concern for collection and storage of personal health information. They do however recognise the possibility for medical and research benefits. Those participants with dependencies on health technologies expressed higher levels of concern for errors in heath data.

5.3.6 Ireland - Trust in Health Platforms

The interviews aimed to gain an understanding of the role of trust when one self-discloses personal health information to digital health platforms. Participants gave responses that focused on predefined themes; competence, benevolence, integrity, design, perceived reputation and information quality.

5.3.6.1 Overall Trust

Overall participants displayed a high likelihood to trust health professionals however this likelihood to trust waned with regard to health technology vendors. Those who displayed high levels of trust in health professionals commented on personal experiences with good health professionals, with only a handful of participants describing bad experiences with 'incompetent' health professionals.

Participants broadly referred to having no trust in health technology vendors. This low level of trust was frequently attributed to commercial endeavours by health technology vendors, using personal data for marketing purposes and not feeling confident that data was being used in a confidential manner. A small number of participants said they would need to consider the company in question before commenting on their likelihood to trust the vendor.

5.3.6.2 Competence

Competence in a health context refers to a health professional's ability to perform their duty, while health platform users seek functionality in health platforms. In this regard participants who had positive experiences with health professionals referred to trusting peoples' abilities, another stating, *"I really believe in them", (p9, Ireland)*. Some others had family members working in the health industry and this helped to strengthen their perceived trust in health professionals. While many referred to trusting people, conversely the few participants that had low trust in health professionals also had bad experiences with health professionals. Some participants had a mixed outlook, specifically if a health professional who was previously unknown to them.

When considering the competence or functionality of technology and health technology vendors the outlook overall was negative. Participants raised doubt that technology vendors and their systems could always be trusted to treat personal data in a confidential matter. The nature of health platforms being online reduced some participants trust due to hearing stories of hacking.

5.3.6.3 Benevolence

Benevolence in a health context refers to a health professional's ability to act in good faith and to the best of their ability, while health platform users seek helpful health platform experiences. Almost all participants believed health professionals acted in good faith, participants tended to trust people.

The same was not the case for health technology vendors and their platforms. Many participants expressed confidence that vendors would *"harvest information in order to inform their own commercial objectives", (p1, Ireland),* as such many participants expressed *"close to zero", (p4, Ireland)* trust in health technology vendors. While trust here was low it is worth noting that nearly all negative responses were based on participants' perceptions and consumption of news content as opposed to direct personal infringements.

5.3.6.4 Integrity

Integrity in a health context refers to the perception that a health professional performs their duty with honesty, while health platform users expect technology solutions to be reliable. In this case again participants displayed high trust in health professionals, believing it is simply part of a health professionals job to have integrity.

While little mention was made to the reliability and integrity of technology vendors, participants did continuously question motives of health technology vendors when collecting personal data.

5.3.6.5 Design

Historically, a number of key design factors have been shown to influence a person's perception of trust in online platforms, from layout, imagery, advertisements to navigation menus. In this given online health context participants showed no deviation from previous research findings.

Almost every participant believed design played a very important role in their perception of trust when considering online health platforms, as one participate put it, *"ease of use is obviously critical" (p3, Ireland).* In one case a participant noted having a *"low tolerance" (p6, Ireland)* for poorly designed systems and would delete any health application that was fitting this description. Presentation of data was also influential for others, as another participant noted the clear data presentation of key health and fitness indicators on Garmin platforms is what convinced the user to stay on the platform.

Significantly, a participant claimed that the usability of a fitness and health monitoring app positively influenced their trust in the app and their usage of the app, yet it was *"hard to say" (p1, Ireland)* if it influenced their self-disclosures on the application. This is despite the fact that the application's service is based on automatically disclosing personal health information to a cloud database in order to supply an analysis back to the user. This was a common response and raises the concept of subconscious self-disclosure of personal health information to online health platforms. In this instance based on participant responses design could be said to influence non-explicit, subconscious disclosures.

One participant who had extensive years of experience with health platforms referred to design having little influence on their likelihood to trust a health platform. This was due a considerable amount of experience with poorly designed health platforms. In this case the participant relied more on access to quality data than an intuitive interface.

5.3.6.6 Perceived Reputation

It has been written extensively that reputation has an influential role in the process of developing trust offline, usually forming over a period of repeated interactions or observations. In an online health context, the process takes on different forms, in this instance participants associated online reputation with their ability to recognise domain names and the ability to consult with online reviews.

Participants reported mixed feelings as to the role of domain names. Over half of all respondents reported being positively being influenced to trust a health platform if it was registered to a domain they were familiar with, .ie and .com being the most commonly referenced. One participant believed a platform with a familiar domain and a secure look to have *"subliminal" (p1, Ireland)* positive effects on them.

A number of participants said domain registration played no role in their likelihood to trust a health platform, while some others would not trust an unknown domain. Other participants relied on reviews more than any other factor when assessing reputation.

5.3.6.7 Information Quality

Participants displayed high regard for the quality of information available via online health platforms. Traditionally, information quality is characterized by features such as accuracy, timeliness, completeness, relevance, and consistency and participants' outlooks did not deviate from previous research.

Participants showed almost zero tolerance for errors in data and attributed this largely to the fact that the discussion involved personal health information, *"If there's errors and you're supposed to be a doctor or a professional, it doesn't look* *good" (P10, Ireland).* Others highlighted the personal necessity of information quality, *"that would affect me negatively because I rely on it for three things" (P5, Ireland).* The below quote captures the dominant outlook of participants in relation to the importance of information quality.

> *"I had a thing recently with Map My Run where it was incorrectly logging my times. So as I am running I know how long it takes. It said I ran the first kilometres in 2 minutes and that I ran another Kilometre 30 seconds later. So there's obviously some kind of error with the software. I just deleted the whole thing, the whole app, because I got frustrated"*
>
> *P1, Counsellor, Ireland*

Regular updates and timeliness also played a significant factor when participants considered the role of information quality and the trustworthiness of a health platform, "if it's well managed and reviewed on a regular basis it would impact me" (P8). While accurate grammar and spelling was also frequently referred to, as evidenced in the below quote.

> *"...definitely grammatical mistakes, and stuff like that. If they don't care about their website enough, I wouldn't trust providing them any information because I don't know if they really care about minute things. When it comes to health, it's really personal."*
>
> *P6, Masters student, Ireland*

5.3.6.8 Review of THP

There is a clear relationship between trust and self-disclosure on online health platforms. Due to the complex nature of trust as a construct this relationship is also complex. Moreover, for the purpose of this study trust was expanded beyond its traditional components (competence, benevolence and integrity) to include those factors that impact trust in an online scenario; design, perceived reputation, and information quality.

A number of observations can be made from the participants' insights. Chief among these is that the presence of the traditional components of trust, competence, benevolence and integrity all play an influential role in one's likelihood to trust a health platform. Where participants deem a platform to have an ability to safely gather, store and use their data they are inclined to use that platform. Conversely if they deem the platform and its vendor unable to perform such duties they are likely to not use the platform. Participants overall considered health professionals to operate with competence, benevolence and integrity, save for a few cases where participants had a personal bad experience with a health professional. Almost all participants struggled to observe these same traits in health technology vendors. In particular participants were unsure of health technology vendors' intentions with user data. That said, some reported satisfactory experiences with vendors.

Design appears to have a considerable influence on participants trust outlook on health platforms, and as a result, on their usage of a platform. Many participants associate ease of use or usability with trustworthy design. If a platform layout is intuitive they appear highly likely to use the platform repeatedly. Conversely, if a platform is difficult to use they are likely to delete it or stop using it. Significantly, it appears as though trustworthy design and automatic health tracking apps blur the lines between usage of a health platform and conscious, explicit self-disclosure of health data. Specifically, it appears as though participants can subconsciously and non-explicitly self-disclose health information if they deem a platform to exhibit good usability traits. Only participants with extensive history of using health platforms disregarded the role of design in likelihood to trust a health platform.

Perceived reputation played a minor role in the development of trust in this instance. That said, familiarity of domains and the availability of reviews had a positive influence on trust. It is not clear that the absence of these would have a significant negative effect on perceived trust.

Finally, information quality appears to play a critical role in one's likelihood to trust a health platform. Errors in data and health information are of critical importance to some and as result participants display little to no tolerance for such issues. If such issues are apparent participants will simply delete an app or cease using a platform. In addition, the absence of care to grammar and spelling signal a lack of care in platform maintenance and as such participants predict a lack of care for the confidentiality of one's personal health information. If poor grammar or spelling is observed many participants would also cease use of a platform.

- **Summary Point: Participants reveal that the link between online self-disclosure and trust in a health platform is dependent on the one's trusting habits and the quality of a health platform. Participants indicate that a trusting nature combined with trustworthy platforms leads to usage of these platforms and as a consequence users' self-disclosure of personal health information. Conversely participants indicate that a trusting nature combined with untrustworthy platforms can lead to disuse of platforms. According to participants, trustworthy design can generate subconscious, non-explicit self-disclosures.**

5.3.7 Ireland - Personality

These interviews aimed to develop an understanding of each participants' personality traits. To do this participants were asked to review the Big-Five personality domains (Gosling, Rentfrow and Swann, 2003). In doing so the interviews further aimed to develop an understanding as to how personality traits related to online self-disclosure of personal health information.

The Big-Five personality research describes all people as having a personality made up of five traits in decreasing order of power (openness, conscientiousness, extroversion, agreeableness, neuroticism). This section will give a brief summary of the most prevalent traits found amongst participants and how they relate to participants' likelihood to self-disclose.

The two highest ranking traits were jointly extroversion and conscientiousness, followed closely by openness, joint lowest ranking were neuroticism and agreeableness. These findings are of note as a review of participants' likelihood to self-disclose reveals a general willingness to self-disclose online but also a regard for the risks associated with online self-disclosure, many claiming only to disclose when necessary or within trusted online communities. These revelations would seem to fit with the predominant traits. Extroversion is associated with sociability, talkativeness, actions and a lack of shyness, while conscientiousness is associated with self-discipline, responsibility, caution and impulse control.

- **Summary point: The greater the presence of extroversion in participants the more likely they are to self-disclose personal health information online. The presence of conscientiousness in participants**

can reduce their likelihood to self-disclose personal health information online, causing one to be risk aversive.

5.3.8 Ireland - Self-Disclosure

The interviews aimed to understand the extent of one's online self-disclosures. As such participants were questioned on their online self-disclosure as it relates to the two significant core dimensions uncovered during the quantitative analysis of self-disclosure; amount and depth.

Participants' initial perceptions of what constituted online self-disclosure varied. Some participants had medical conditions which required them to log digital data on a regular basis, usually daily. This data would then be disclosed exclusively to a doctor and in some cases to an online medical community. In addition, most of these participants used digital devices that automatically disclosed their health information to a private company's cloud servers.

Participants without acute medical conditions all regularly used fitness and wellness tracking devices. While many of these participants disclosed their health information from these devices with online communities not all of them were aware that disclosure of their health data was also occurring regularly via automated transfer of health data to a company's private cloud, *"I never really thought of that as disclosing my health information online", (p10, Ireland).*

5.3.8.1 Amount

Amount refers to whether a communicated disclosure of personal experience or information occurs frequently or infrequently and also to the duration of time over which it occurs. Due to the nature of participants' digital health devices almost all participants exhibited regular disclosures of health information whether it was in the form of a communication with a medical professional, an online health community or to a health technology venders cloud server. One participant who recorded and disclosed fitness data said, *"I'd say on a yearly basis, it would kind of work out of maybe three or four times a week, but during summer nearly every day, more time to go to the gym and to be healthy, to eat well".* This statement reflected the majority of participants' responses with regard to fitness and wellness devices. Participants with medical conditions exhibited more periodic disclosures, *"I wouldn't really log on and physically input anything but I would plug my watch into my computer once a week so once a week it goes into to the cloud.", (p8, Ireland).*

5.3.8.2 Depth

Depth refers to whether or not a communication reaches a degree of intimate revelation, depth and intimacy can be integral to developing relationship closeness and penetration of a network. Participant outlook with regard to depth varied. The majority did not feel that the nature of their disclosures were very intimate, some thought it would feel more intimate if they thought others had access to their data, others simply never took the time to consider if their data was intimate and some claimed their data not to be intimate as they believed it to be stored as non-identifiable or metadata. Interestingly some participants felt the interpretation of intimacy in health data to be subjective, as outlined below.

> *"I think that's quite a subjective thing. I mean when I was using these apps I wasn't really thinking about how I've disclosed my information here. I was thinking about how was my sleep last night."*
>
> *P1, Counsellor, Ireland*

For the majority, fitness data was not viewed as intimate however some fitness loggers and those with medical conditions did consider heart rate and blood pressure information to be of an intimate nature, *"Well the sleep and the walking would be just general but I'd say the heart rate would be personal", (p5, Ireland).* Additionally, some participants exhibited a growing concern for what could be deemed as having depth or intimacy, as evidenced below.

> *"Maybe you could say there's depth to it. If someone was to access that they'd be able to see what products I'm eating, how many steps I'm taking every day. We had a workshop today on Tableau. And the lecturer was telling us just by him looking at someone's data usage he could tell where they lived and what they did. I suppose that if someone could access your steps they might find out when you're not at home."*
>
> *P10, Masters student, Ireland*

- **Summary point: due to the nature of health tracking devices participants disclose often and on a continuous basis. Participants' definition of depth and intimacy vary, however on the whole fitness and wellness data is not considered intimate but heart rate, blood pressure and health condition data is considered intimate. Almost all participants were unaware that their health tracking devices are automatically disclosing their data to cloud servers.**

5.3.9 U.S. - Reciprocity

The interviews aimed to gain an understanding of participants' feelings about reciprocity. Specifically, participants discussed whether reciprocity influenced their THP and whether it influenced their HIPC. During the interviews participants discussed reciprocity from the perspective of others' expectations of them to reciprocate interactions and sharing of personal health data, whether others trust them to reciprocate sharing and interaction, and whether it is only fair that users reciprocate sharing and interaction on digital health platforms.

Overall participants displayed mixed feelings towards the role of reciprocity in the disclosures of personal health data. While some participants displayed no desire nor expectation to reciprocate the sharing of personal health information, others simply do not feel to be an obligation to reciprocate the sharing of personal health information. Two participants alluded that reciprocation of personal health information was only necessary in the case of targeted medical research projects.

5.3.9.1 Expectation belief

Similar to Irish data, US participants displayed little to no obligation to reciprocate based on the belief that others expected them to, as evidenced in the following quote.

"I can only speak for myself. I have no expectation of anyone else. I only control my own data. If I'm giving my information, I don't do it with the expectation that everybody else is going to do the same."

P1, Software Developer, U.S.

This was the majority outlook with regard to expectation belief however two participants displayed a more nuanced outlook, believing that some people share with an expectation for recognition, as outlined in the statement below.

"They're obviously posting online for some recognition. In a sense."

P7, Masters Student, U.S.

5.3.9.2 Trusting expectations of others

Similar to Irish data, participants' attitude towards trusting expectations was similar to expectation belief. The majority of participants did not believe that others would trust them to reciprocate experiences and personal health information. However, a select few did indicate that people close to them may have a trusting expectation of reciprocal sharing of health information, as shown in the following statement.

"I definitely think my closest friends would trust that. But if I have acquaintances I probably wouldn't go that far."

P6, Undergraduate, U.S.

Despite this the majority of participants did not believe that others would expect them to reciprocate sharing of heath data, indeed most saw it as unnecessary due to the nature of personal health issues, as was clearly expressed in the following observation.

"Why would they? We all have different health needs."

P8, Self-employed, U.S.

5.3.9.3 Fairness

Echoing Irish participant outlooks, the vast majority of participants did not believe it to be only fair that they should reciprocate and disclose personal health information on digital health platforms if other people do. Many believed there was no expectation of fairness, that there was no social contact or agreement. Indeed, none of the participants departed from the opinion that fairness played no role. Instead they insisted that it was an individual choice, *"I think everyone has their own* *free will to post whatever they want to." (p4, U.S.).* This sentiment was echoed again in the following statement.

> *"Absolutely not. That's a personal choice and no one but myself can determine what to do with my information."*
>
> *P8, Self-employed, U.S.*

5.3.9.4 Review of reciprocity

The overall outlook regarding reciprocity is very similar to the Irish data. U.S. participants see no strong expectation of reciprocity. A select few believe that family and close friends might trust them to reciprocate health information sharing while other do not believe that health information sharing should carry any expectation of reciprocation due to the personal nature of health issues. All participants consider that act of reciprocation of health data sharing to be a individual choice without obligation. No participant referred to HIPC when discussing reciprocity.

- **Summary point: Participants reveal that the link between trust and reciprocity in the given context is evident but low. Participants indicated that levels of reciprocity can grow when family or close friends are the information receivers. Participants regard reciprocity as an individual choice without an obligation. Privacy concerns do not appear to play a significant role in participants' reciprocation behaviour.**

5.3.10 U.S. - Social Influence

The interviews aimed to gain an understanding of participants' feelings towards social influence and its role in trust development and impact on HIPC. Specifically, participants discussed whether encouragement from those close to them influenced their trust and self-disclosures, if the benefits others share influences them, if health professionals' encouragement plays an influential role and if social influence had any role in their HIPC. The findings aligned strongly with those found among the Irish participants in that social influence was present but varied in its significance across four main areas with will now be presented.

5.3.10.1 Encouragement from Close Friends or Family

As with Irish participants, almost every participant could refer to a personal anecdote of friends or family members encouraging them to use or consider using a health platform. In most cases this encouragement was due to perceived and observed health and fitness benefits on the part of the family member or close friend. Ever participants referred to having open discussions with close family or friends and seen in the following example.

"I think people might recommend things that they are using or they have had good luck with and we might discuss that. Like the ramifications of that app or their experience with that and we might talk about it in the context of society in general"

P2, Communications Professional, U.S.

5.3.10.2 The Benefits of Others

Echoing Irish participants, every participant signalled that those around them garner benefit from health platforms and as such this has positively impacted their adoption of health platforms. The benefits perceived and obtained varied but the majority of participants listed routine monitoring of healthy habits such as exercise, regular heartbeat and diet. Others referred to benefits beyond tracking of fitness data, to management of an illness. Some participants noted that their families share data and useful health information through these health platforms. The widespread use of Fitbits and fitness platforms was evident in almost every interview as exhibited below.

"Mostly they use them for tracking things like their diet, exercise, or in the case of one of my aunt, for tracking her diabetes statistics."

P8, Self-Employed, U.S.

Of note however, some participants expressed scepticism as to how sustainable the benefits derived from fitness apps might be, as seen in the following statement.

"Yes. I think that it encourages lifestyle shifts for short periods of time. I don't know if I've ever observed someone changing their life super sustainably. I think it helps people on shorter doses as it pertains to fitness and diet, but I'm not sure I'm convinced that it's like the most sustainable way to make significant lifestyle changes. I've observed friends using a diet related app for a chunk of time or a fitness app for a chunk of time and then it kind of peters out. That's like my general impression."

P2, Communications professional, U.S.

5.3.10.3 Status Symbol

Participants displayed mixed feelings as to whether one could derive status from sharing health information. While some participants believed it to be possible to achieve status simply because *"because it is trend nowadays" (p9, U.S.),* others were reluctant to attribute status to those sharing health information as evidenced in the following quote.

"Not really. I do it for myself I don't really do it for anyone else."

P8, Self-Employed, U.S.

Many participants claimed to have never thought of health information sharing as something that could create status but one participants did opine that "…w*e scroll so much and influencers, they influence you in the way that maybe a doctor would or another person of actual status in the society would" (p2, U.S.).*

5.3.10.4 Encouragement from Health Professionals

Every participant expressed that if a health professional encouraged them to adopt a health platform they would indeed consider it. All participants said they would happily consider a suggestion from a health professional, two participants indicated that they already have taken on such a suggestion.

5.3.10.5 Review of Social Influence

The role of social influence as it relates to THP is clear and evident. Almost every participant could recall a friend or family member encouraging them to use a health platform and as such the vast majority of participants took up the use of a health platform or device. In many cases this take up translated into regular sharing of health data and useful health information amongst trusted communities. Further to this all participants indicated that should a health professional encourage the use of a health platform they would consider this suggestion.

With regard to the benefits others gain from health platforms, again almost all participants had experience of those close them gaining benefits. These benefits ranged from daily health and fitness improvements to quality of life and diabetic tracking.

Participants had mixed views as to whether one could gain status from usage of health platforms. Notably, any status symbol development might be enhanced with disclosure of health and fitness data to more traditional social media platforms. No participant referred to social influences having an impact on HIPC, positive or negative

- **Summary point: the link between social influence and THP is clear and evident amongst participants. According to participants health professionals, family and close friends can influence one's likelihood use a health platform and to therefore disclose personal health information within trusted communities. The participants have observed health and fitness benefits and indicate that this observation can positively influence one's likelihood use a health platform. Participants indicate the status can be achieved by disclosing health information in both open and closed digital communities. Participants made no reference to social influence having any impact on HIPC.**

5.3.11 U.S. - Privacy Risk Belief

The interviews aimed to gain an understanding of participants' privacy risk beliefs and their influence on THP and HIPC. Specifically, participants discussed their perception of risk when sharing information online, if they believed there to be potential for loss when sharing information online, and finally if they feel safe when sharing information online.

Every participant acknowledged that there is an inherent risk sharing information online, moreover some participants agreed there to be a potential for loss when disclosing information online, though the risk and potential varied. Almost every participant expressed not feeling safe when sharing information online however this feeling varied in degree from person to person. The following sections will look at these three components individually.

5.3.11.1 Perception of Risk

All participants agreed that there is risk involved with sharing personal information online. Of note all participants indicated that risk varied based on the type of information being shared. All agreed that generic personal data was on little concern when shared online but as one participant noted (below) if more specific data was shared this could lead to negative outcomes such as discrimination.

> *"I think that there's some personal information that should probably not be shared. I mean to a certain extent you need a lot of that to be shared like I know for public health information like it's good to keep some of the data out there. You know just keep the community safe. But then there's other times where like if it is a genetic case and if you needed to or if you'd like a rare genetic condition and it got out and it somehow impacted you in some way that could potentially be not as great because then you know you have random people coming to you asking questions or some sort of discrimination."*
>
> *P5, Biomedical Informatics Student, U.S.*

5.3.11.2 Potential for Loss

Most participants recognised a potential for loss when sharing data online however the perception of loss varied among participants. When some saw high potential for loss such as discrimination others felt indifferent. The predominate outlook on the matter is displayed in the following statement.

"Yeah like identity theft is huge. If you give them your information like your Social Security number which you should never ever do, then yeah they could steal everything that you have."

P4, Research Assistant, U.S.

Others however while acknowledging the potential for loss simply did not care and did not believe any loss could have a negative impact on them.

"Yes and no again. If they can use that information for something, Yeah. If again it's just steps, I don't think they could do anything with that."

P6, Undergraduate, U.S.

5.3.11.3 Safe online

Echoing the Irish experience, the majority of participants referred to not always feeling safe when disclosing information online however all participants were still happy to share information online. The majority of participants displayed an appreciation for different types of data and different levels of data vulnerability, as outlined in the following quote.

"Yes, I mean, I think it comes back to what we were talking about earlier. I think it largely depends on who you're giving it to. Like, if it's a brand that I know and that I trust, if it's information that I don't feel is super sensitive, then I feel comfortable with it. If they're asking me for my Social Security number and it's somebody that I don't know, then I wouldn't do it."

P1, Software Developer, U.S.

Of note participants continually referred to trusting some digital platforms when they share data, namely social media platforms, as opposed to less recognised companies or brands, *"…if I trust the website or the company that I am interacting* *with, and it's on a secure server and I know how my information is being used then I am comfortable with sharing certain details…" (p8, U.S.).*

5.3.11.4 Review of Privacy Risk Belief

It is evident that all participants believe there is a risk when one discloses information online. As to the nature of the risks almost all believed identity theft to be a clear danger but that some greater risks also exist such as discrimination. Participants referred to trusting some social media platforms when sharing data and claimed that they would not share personal data with unrecognised brands or companies. Finally, almost all participants agreed to feeling unsafe at times when disclosing information online but for almost all participants this feeling was context specific. While some indicated that they would withhold certain information online all continued to share regularly indicting the possible presence of a privacy paradox.

- **Summary point: while privacy risks are acknowledged by participants they do little to deter trusting behaviours. Some participants indicated that risk beliefs can play a role in their HIPC. According to participants, risk is considered directly proportional to an individual's online safety competence.**

5.3.12 U.S. - Health Information Privacy Concerns

The interviews aimed to develop an understanding of users' health information privacy concerns, how they impact THP and consequently self-disclosure. All participants expressed a concern for privacy as it relates to health data. The level of concern varied on a case by case basis and for some participants' concern pertained only to the future as data collection habits increase. Each dimension of HIPC will now be discussed in this section.

5.3.12.1 Collection

Collection refers to the frequent and large collection of health data that is stored digitally. Almost every participant expressed unease with vast amounts of health data being stored, though almost all also agreed that there can be targeted research benefits to such actions when undertaken by the correct bodies as expressed in the following statement.

"I think I feel overwhelmed by it. I don't have a strong understanding of how it can be used, so I think it makes me nervous. But I'm also interested I think it's interesting. I'm interested in what we could possibly learn from that and how it could be used in a positive way. But I'm nervous about the negative. I can see the benefit, but I'm also nervous about the risks."

P2, Communications Professional, U.S.

The majority of participants admitted to not having considered the implications of large quantities of their health data being stored by public and private entities. Participants also alluded to having to contend with future concerns for their health data.

"I never really thought of it that way I always thought sharing information will be like, you know those questionnaires like are you on blood pressure tablets? Under medication? Have you ever suffered from this? I never really thought like having an app that monitors your steps would... like I never saw it as a big deal or anything... I suppose if I had to really think about it I wouldn't want people just to be able to see my information whenever they want. But then there is another sense I'm not that concerned about right now. I think I could be in the future"

P7, Masters student, U.S.

- **Summary point: participants express concern for collection and storage of personal health information. They do however recognise the possibility for medical and research benefits. They express distrust of private companies' collection and storage of personal health information. Participants continue to disclose health information despite HIPCs. Participants want personal health information to be strongly secured and regulated.**

5.3.12.2 Unauthorised Secondary Use

Unauthorised secondary use refers to user's concern that health data might be used for secondary purposes. Almost every participant expressed a concern for unauthorised secondary use of their personal health data, especially when it is used for targeted advertising, "… *I worry about advertising all the time, and I get freaked out when things follow me around the Internet that are connected to various data that I've shared online" (p2, U.S.).* Other expressed a more severe outlook, *"… that information is mine to disclose, it belongs to me and using it without my permission is akin to stealing from me", (p8, U.S.).*

Other participants shared less concerns for unauthorised secondary use of their data and view it as a possible utility for future public health concerns, as seen in the following quote.

> *"I am not worried right now and I don't think I will be. I think we might have a special situation in the future, say primarily for public health reasons. So if you have a strange disease that's very infectious and that's a threat to the community. Then officials would need to know at that point."*
>
> *P5, Medical Informatics Student, U.S.*

- **Summary point: participants displayed concern for secondary use of their health data, particularly in the future as data collection grows. Participants did however appreciate that there are medical and research benefits to secondary use of personal health data. Participants distrust targeted advertising arising from their data. Any secondary use should be restricted and used by public health entities only.**

5.3.12.3 Improper access

Improper access refers to user's concern that their health data might be accessed by unauthorised parties. While all participants expressed concern regarding improper access the nature of this concern varied greatly. Similar to the Irish experience, many expressed concern for unwanted access to their health data, be it from individuals or private entities, but freely admitted that this concern was due to a lack of understanding about the protections around their data and how it can be a processed.

"I think it's a general concern I have about all of my data online. Again, I don't understand what those negative forces are and how they might impact me, but I think it's just a general concern that I have. But I'm not concerned enough to have taken any specific action. Does that make sense? For me, I don't know what the steps forward would look like, and I feel overwhelmed by them. Like the idea of protecting my data sounds like a lot of work, and it sounds like something I don't care very deeply about at this point because those negative forces aren't terribly clear to me. But I wouldn't be opposed to taking those steps if it was easy and made sense."

P2, Communications Professional, U.S.

Other participants expressed concern that improper access to their data could result in negative health outcomes if their data was altered,

"I am a little concerned about that. Knowing that people can breach data internally and change records"

P3, Hospital Recruiter, U.S.

Summary point: participants express concern for to improper access to their health data. Participants feel overwhelmed by the dangers and steps required to protect their data.

5.3.12.4 Errors

Error relates to users' concern as to the possibility of errors in their health data. Participants expressed a concern for errors in their personal health data but similar to other HIPC dimensions this concern varied from strong concern to minimal concern. Those most concerned with errors were both dependant on medical devices and working or studying in healthcare. Concerns varied from being prescribed the wrong medication to a device not accurately monitoring their physiological conditions, *"I'm allergic to penicillin so if they didn't have that information that would be concerning", (P3, U.S.).* Some participants simply had little to no consideration for the matter, *"No, I mean, I don't think about that a ton." (p1, U.S.).*

Others noted that while there are many benefits for mobile health apps they should not be considered a substitute for accurate measurements available from a doctor or hospital.

"…a little bit because I know this isn't completely accurate. Even with the heart rate app or any of that it's not completely accurate. So I don't think that it should be used as a surrogate for the accurate measurements that we do take at the doctor's office or at the hospital."

P4, Research Assistant, U.S.

Summary point: participants expressed concern for errors in health data but the level of concern varied depending on personal background and individual reliance on accurate health records.

5.3.12.5 Control

Control refers to users' belief or lack thereof that they have control over their health data. Almost all participants claimed a lack of control over their own personal health data. Of those who expressed a lack of control their desire was to have almost total control over their data, as detailed in the following,

"Do I have control over it? No. I think I should be able to decide whether or not I want that to be shared or used."

P2, Communications Professional, U.S.

A number of participants expressed frustration with the lack of control they have over their health data and also with the systems in place to contain this data,

"I know one of my doctors still uses paper records. Somebody else uses something else so I don't feel like it's where I can control it myself. It's more like I would have to go

somewhere to find the person that is in control, gather it, bring it back in and assemble it all."

P5, Medical Informatics Student, U.S.

- **Summary point: participants feel they have a lack of control over their health data. They would like greater control over who can see and use their health data. A small number of participants feel they have adequate control.**

5.3.12.6 Awareness

Awareness refers to user's awareness of how their personal health information is used and protected. Most participants claimed to be knowledgeable as to how their personal health information is used and protected however no participant was able to elaborate on the matter.

"To the best of my knowledge, yeah. What I mean is I know where I've shared my information."

P5, Undergraduate, U.S.

Indeed, their lack of awareness is evidenced by their almost uniform inability to elaborate on the topic. Echoing the Irish experience, the most common response being, *"I think that people should be more aware of where their data is going", (p3, U.S.).*

- **Summary point: participants appear to have almost no awareness as to how their personal health information is used and protected. This however has done little to impact their likelihood to disclose personal health information. Participants did display a strong desire to have**

greater knowledge and control over how their personal health information is used and protected.

5.3.13 Review of HIPC

Every participant expressed concern for their personal health information however, the level of concern varied. Almost all participants claimed to distrust private companies having access to their personal health data but the concern was lower in those who had acute dependencies on health technologies.

All participants claimed to have concern for how their data was collected, stored, used and control. Only those with acute dependencies on health technologies expressed high levels of concern for errors in heath data. These concerns did nothing to change their information sharing behaviours. Participants claimed to be overwhelmed by the steps required to secure their health data and are concerned with future threats to their data.

The combination of concern for privacy, expressed distrust of health technology vendors and continued health disclosure behaviour raises the question of the privacy paradox being present in these findings.

- **Summary point: participants all express concern for their health data and a lack of trust in health technology vendors yet they all continue to self –disclose. Participants are overwhelmed by the steps required to secure their data and are concerned with future threats to their data. Participants expressed concern for errors in health data but the level of concern varied depending on individual digital skill competencies. Participants express concern for collection and storage of personal health information. They do however recognise the possibility for**

medical and research benefits. Only those participants with acute dependencies on health technologies expressed high levels of concern for errors in heath data.

5.3.14 U.S. - Trust in Health Platforms

The interviews aimed to gain an understanding of the role of trust when one self-discloses personal health information to digital health platforms. Participants gave responses that focused on predefined themes; competence, benevolence, integrity, design, perceived reputation and information quality.

5.3.14.1 Overall Trust

Overall participants displayed a trusting nature. They were likely to trust health professionals however this likelihood to trust waned with regard to health technology vendors. Those who displayed trust in health professionals commented on personal experiences with good health professionals.

Participants broadly referred to having no trust in health technology vendors. This low level of trust was frequently attributed to commercial endeavours by health technology vendors and hearing of regular data breaches in large technology companies. A small number of participants said they would need to consider the company in question before commenting on their likelihood to trust the vendor.

Every participant indicated that design of digital health platforms (DHPs), their reputation and the quality of information provided by DHPs played a significant role in their likelihood to the trust a DHP.

5.3.14.2 Competence

Competence in a health context refers to a health professional's ability to perform their duty, while health platform users seek functionality in health platforms. In this regard participants who had positive experiences with health professionals referred to trusting peoples' abilities. Most participant were more trusting of health professionals than DHPs, *"I trust them more than I trust online apps", (p1, U.S.),* Some participants had a mixed outlook as to whether health professionals would have the competency to protect user data, as one participant claimed,

> *"I don't think I would trust my health professionals to have a high degree of understanding of this space and of the possible repercussions…Because they're not technologically inclined and it's not their expertise in any shape or form."*
>
> *P2, Communications Professional, U.S.*

When considering the competence or functionality of technology and health technology vendors the outlook overall was negative. Participants raised doubt that technology vendors and their systems could always be trusted to treat personal data in a confidential manner. The nature of health platforms being online reduced some participants trust due to hearing stories of hacking.

> *"…because you see it in the news that all these companies have big data breaches and then there's like yesterday that news came out said that Facebook had an issue where they put everyone's stuff on public instead of private, saying they made the mistake. There's just so much of that, so many examples of them messing up."*
>
> *P4, Research Assistant, U.S.*

5.3.14.3 Benevolence

Benevolence in a health context refers to a health professional's ability to act in good faith and to the best of their ability, while DHP users seek helpful platform experiences. Almost all participants believed health professionals acted in good faith, participants tended to trust people.

Despite claiming not to trust health technology vendors and their platforms some participants expressed having had positive, helpful experiences with DHPs.

"I actually do trust some, I feel like they put a lot of effort into keeping my information private and I don't really have too much of a fear of them disclosing that information to the public."

P3, Hospital Recruiter, U.S

One participant noted that unhelpful DHPs caused them to be wary of them,

"Depends some are a little scary because they don't seem fully put together. Those are the ones I'm wary of."

P5, Medical Informatics Student, U.S.

5.3.14.4

Integrity

Integrity in a health context refers to the perception that a health professional performs their duty with honesty, while DHP users expect technology solutions to be reliable. In this case again participants displayed trust in health professionals, believing it is simply part of a health professionals job to have integrity.

With regard to reliability and integrity of technology vendors, participants did question motives of health technology vendors when collecting personal data. Some participant claimed that they would alter their disclosure behaviour if they believed a technology vender to be untrustworthy, as evidenced below.

"I feel like I would describe it as kind of like optimistic indifference. If I strongly distrusted them, then I would actively not give them my information. I would actively try to get information back that I already have given. I don't actively trust them. I just kind of generally trust the universe and cross my fingers that they're doing okay things with my data."

P1, Software Developer, U.S.

Others were impacted by societal events in the U.S. One participant described how institutional issues had eroded their generally likelihood to trust technology companies and public institutions as a result of the Cambridge Analytica news event, as outlined below.

"I think that's changed significantly over the past five years. I think five years ago I wouldn't have had significant concerns. I think based on current events and how they dealt with the political situation in the United States, it's pretty fraught right now. And technology companies don't have answers very readily available, and they're not building trust in very real ways. So I think that's degraded my level of trust in general. But I also have a lot of hope."

P2, Communications Professional, U.S.

5.3.14.5 Design

Historically, a number of key design factors have been shown to influence a person's perception of trust in online platforms, from layout, imagery, advertisements to navigation menus. As with the Irish data, participants showed no deviation from previous research findings.

Almost every participant believed design played a very important role in their perception of trust when considering online health platforms, as one participate put it, *"…I actually like the ease of use of the platform, it makes it easier to trust in them." (p3, U.S).* This message was echoed by another participant how explained that design was a significant factor in their likelihood to trust and subsequently use a DHP.

> *"I think that's probably a big part behind my trust actually because a lot of times if they have a weird Website or App that I can't navigate then it's like well you can't put together a cohesive website then why am I going to trust you. But if you have thought it through then I guess that I'm more inclined to spend more time with that page and maybe learn more about the company, as I learn more I might trust them more and more if that makes sense."*
>
> *P5, Medical Informatics Student, U.S.*

The majority of participants made reference to the importance of design when establishing trust.

> *"Of course, the more professional an app or website looks, the more trustworthy it appears. If the app is of poor quality, slow, and badly designed it certainly would make a person think twice about sharing information."*
>
> *P8, Self-employed, U.S.*

One participant claimed that design did not impact their likelihood to trust a DHP but rather their likelihood to use one, as explained below.

> *"I don't know if it influences my willingness to trust them. I think it influences my willingness to use them. Part of the reason I stopped using Fitbit is because of the app. If I wanted to see my steps over the last six months charted, they made it really hard to do. So it didn't make me not trust them. It just made not use it. If I had to do four tasks to get to the thing I wanted, then it's a waste the time."*
>
> *P1, Software Developer, U.S.*

5.3.14.6 Perceived Reputation

It has been written extensively that reputation has an influential role in the process of developing trust offline, usually forming over a period of repeated interactions or observations. In an online health context, the process takes on different forms, in this instance participants associated online reputation with brand recognition, their ability to recognise domain names and the ability to consult with online reviews.

Participants reported mixed feelings as to the role of domain names. Over half of all respondents reported being positively being influenced to trust a health platform if it was registered to a domain they were familiar with, .org and .gov being the most commonly referenced, see an example below.

"Think we're kind of trained to trust gov.org more. I guess there are country extensions that maybe I would trust less if I were less familiar with them."

P1, Software Developer, U.S.

Other participants associated reputation with social recommendations,

I think I said earlier, I'm much more likely to use something and trust something if it's been recommended to me or if it's been recommended by some other platform that I trust.

P2, Communications Professional, U.S.

A number of participants said domain registration played no role in their likelihood to trust a health platform, while some others would not trust an unknown domain. Other participants relied on reviews more than any other factor when assessing reputation.

5.3.14.7 Information Quality

Participants displayed high regard for the quality of information available via DHPs. Traditionally, information quality is characterized by features such as accuracy, timeliness, completeness, relevance, and consistency and participants' outlooks did not deviate from previous research.

As was the case with the Irish data, participants showed almost zero tolerance for errors in data and attributed this largely to the fact that the discussion involved personal health information, *"If it's low quality information I would not interact with it, I would not interact with something if there are grammatical errors" (p2, U.S.).* Others highlighted noticing low quality issues regularly, *"I'm laughing because I see it a lot on websites, grammatical errors and lack of updates and stuff, so I also look for that and the website to be updated" (p6, U.S.).* The below quote captures the dominant outlook of participants in relation to the importance of information quality.

> *"Quite a bit. If a company is professional, they wouldn't have excess errors or incorrect information. One or two errors are fine, but if it's a mess I would certainly reconsider using it."*
>
> *P8, Self-Employed, U.S.*

5.3.14.8 Review of THP

As was the case with the Irish data, there is a clear relationship between trust and self-disclosure on DHPs. Due to the complex nature of trust as a construct this relationship is also complex. Moreover, for the purpose of this study trust was expanded beyond its traditional components (competence, benevolence and integrity) to include those factors that impact trust in an online scenario; design, perceived reputation, and information quality.

According to the American data the traditional components of trust, competence, benevolence and integrity all play an influential role in one's likelihood to trust a health platform. Where participants deem a DHP to have an ability to safely gather, store and use their data they are inclined to use that platform. Conversely if they deem the platform and its vendor unable to perform such duties they are likely to not use the platform. Participants overall considered health professionals to operate with competence, benevolence and integrity. Almost all participants struggled to observe these same traits in health technology vendors. In particular participants were unsure of health technology vendors' intentions with user data. That said, some reported satisfactory experiences with vendors.

Design appears to have a significant influence on participant's likelihood to trust DHPs and on their subsequent usage of a DHP. Many participants associate ease of use or usability with trustworthy design. If a platform layout is intuitive they appear highly likely to use the platform repeatedly. Conversely, if a platform is difficult to use they are likely to stop using it.

According to participants perceived reputation played a significant role in the development of trust in DHPs. Familiarity of domains, social sharing, brand recognition and the availability of reviews had a positive influence on trust.

Finally, information quality appears to play a critical role in one's likelihood to trust a DHP. Errors in data and health information are of critical importance to some and as result participants display little to no tolerance for such issues. If such issues are apparent participants will cease using a platform. In addition, the absence of care to grammar and spelling signal a lack of care in platform maintenance and as such participants predict a lack of care for the confidentiality of one's personal health information. If poor grammar or spelling is observed many participants would also cease use of a platform.

- **Summary Point: Participants reveal that the link between online self-disclosure and trust in a health platform is dependent on and individual's trusting habits and the quality of a health platform.**

Participants indicate that a trusting nature combined with trustworthy platforms leads to usage of these platforms and as a consequence users' self-disclosure of personal health information. Conversely participants indicate that a trusting nature combined with untrustworthy platforms can lead to disuse of platforms. According to participant responses a trustworthy design can generate subconscious, non-explicit self-disclosures.

5.3.15 U.S. - Personality

These interviews aimed to develop an understanding of each participants' personality traits. To do this participants were asked to review the Big-Five personality domains (Gosling, Rentfrow and Swann, 2003). In doing so the interviews aimed to develop an understanding as to how personality traits related to online self-disclosure of personal health information.

The Big-Five personality research describes all people as having a personality made up of five traits in decreasing order of power (openness, conscientiousness, extroversion, agreeableness, neuroticism). This section will give a brief summary of the most prevalent traits found amongst participants and how they relate to participants' likelihood to self-disclose.

The two highest ranking traits were conscientiousness and agreeableness, followed closely by openness then extroversion. The lowest ranking trait was neuroticism. These findings are of note as a review of participants' likelihood to self-disclose reveals a general willingness to self-disclose online but also a regard for the risks associated with online self-disclosure, many claiming only to disclose when necessary or within trusted online communities. These revelations would seem to fit with the predominant traits. Agreeableness is associated with trusting others and being less suspicious of their environment while conscientiousness is associated with self-discipline, responsibility, caution and impulse control.

- **Summary point: The greater the presence of agreeableness in a participant the more likely they are to feel safe to self-disclose personal health information online. The greater the presence of conscientiousness in a participant can reduce their likelihood to self-disclose personal health information online, causing one to be risk aversive.**

5.3.16 U.S. - Self-Disclosure

The interviews aimed to understand the extent of the participants online self-disclosures. As such participants were questioned on their online self-disclosure as it relates to two significant dimensions uncovered during the quantitative analysis of self-disclosure; amount and depth.

Participants' initial perceptions of what constituted online self-disclosure varied and as such so did their perception on how much data they were disclosing. Many were unaware of their disclosures due to automated fitness devices. Most participants used digital devices that automatically disclosed their health information to a private company's cloud servers. While many of these participants disclosed their health information from fitness devices with online communities not all of them were aware that disclosure of their health data was also occurring regularly via automated transfer of health data to a company's private cloud. When discussing depth of disclosures participants varied in their perception of what intimate data was. For example, almost all agreed that steps on a fitness device was not intimate but that the location data coupled with steps and heart rate could be considered to be intimate.

5.3.16.1 Amount

Amount refers to whether a communicated disclosure of personal experience or information occurs frequently or infrequently and also to the duration of time over which it occurs. Due to the nature of participants' digital health devices almost all participants exhibited regular disclosures of health information whether it was in the form of a communication with a medical professional, online appointment systems, an online health community or to a health technology venders cloud server. The following quote is representative of participants' disclosure activity.

"So I have the Apple Watch and I use the Apple Health Service and I'm also part of a Facebook group where a group of friends talk a lot. Sometimes we talk a lot about life, mental health. Then I have another app to track my menstrual cycle."

P4, Research Assistant, U.S.

Other participants alluded to not wanting to disclose health information regularly but not being able to avoid it due to the nature of fitness apps and lifestyles, the following quote is from a tri-athlete.

"I try very hard not to. I just don't want all my information going on there like we're in the data sharing age and you know the government already knows a lot about me. I just don't want them to have more than they need. I do use the Garmin app and it mainly just tracks my steps. And any physical activity I've been doing."

P5, Medical Informatics Student, U.S.

5.3.16.2 Depth

Depth refers to whether or not a communication reaches a degree of intimate revelation, depth and intimacy can be integral to developing relationship closeness and penetration of a network. Participant outlook with regard to depth varied. The majority did not feel that the nature of their disclosures were very intimate, some thought it would feel more intimate if they thought others had access to their data, others simply never took the time to consider if their data was intimate. American participants had more experience than Irish participants when sharing medical information online, due to an extensive digital health ecosystem in the U.S. As such every U.S. participant had shared private medical information with online Doctors and appointment systems. Participants with health issues considered this to be, *"...very personal...", (p7, U.S.)* data*.* The following quote offers further example of these disclosures.

"They'll ask me what medications I've used in the past. What I'm allergic to."

P3, Hospital Recruiter, U.S.

Participants did not consider fitness data to be intimate, however when fitness data was coupled with location data this worried participants and as such many of the participants considered location data combined with fitness data to be intimate, *"...I guess I would consider heart rate, steps and location intimate", (p1, U.S.).*

Of note one participant referred to sharing DNA data with a DHP for family history purposes. The participant considered this data to be very intimate and indicated that they may have future regrets about sharing such intimate data.

"I suppose the DNA, I thought about that after the fact and thought I maybe regret that. I don't know how that could manifest itself later on, but if I were to do it again, I probably wouldn't have shared that information."

P2, Communications Professional, U.S.

The same participant expressed concern for the revelation of such intimate data and how it could be used to discriminate minority groups.

> *I'm not a minority ethnically or racially, whereas for example, X's family is Jewish. And Jews in general might be much more sceptical about giving their DNA and their health information because historically they've been marginalized in such a real way.*
>
> *P2, Communications Professional, U.S.*

- **Summary point: due to the nature of health tracking devices participants disclose often and on a continuous basis. Participants' definition of depth and intimacy vary, however on the whole fitness and wellness data is not considered intimate but heart rate, location data, DNA and health condition data is considered intimate. Participants believed intimate health data could be used to discriminate or cause harm. Almost all participants were unaware that their health tracking devices are automatically disclosing their data to cloud servers.**

5.4 Integrated findings

Following guidelines by Teddlie and Tashakkori, (2009) the following section integrates the quantitative and qualitative findings to arrive at conclusions for each key relationship. Two steps were undertaken to achieve data integration, first quantitative and qualitative data were integrated by following a triangulation process as outlined by O'Cathain, Murphy and Nicholl, (2010). During this process each construct was reviewed to determine if the findings from both methods were complementary, convergent or dissonant. Where findings were found to be similar they were deemed complementary. Where findings were found to enhance understanding when combined they were deemed convergent. Where findings were found to offer differing views they were deemed dissonant. Second, the integrated findings were used to develop meta-inferences that bring together findings from the two separate methods (Venkatesh, Brown and Bala, 2013).

In order to achieve validity during data integration three criteria were adhered to; integrative efficacy, integrative correspondence and inference transferability (Venkatesh, Brown and Bala, 2013). Integrative efficacy refers to the quality of contrast and comparison when bringing both methods together. The triangulation process set out by O'Cathain, Murphy and Nicholl, (2010) was used to achieve integrative efficacy. Integrative correspondence refers to whether the appropriate research methods were utilised so as to satisfy the aim and purpose of the study. This study aimed to understand what factors influence user self-disclosure of personal health information on DHPs. A number of research calls had been made to address such issues (Bélanger and Crossler, 2011; Venkatesh, Brown and Bala, 2013; Lowry, Dinev and Willison, 2017). Moreover, the dearth of research in the area using a mixed methods research approach was also highlighted in these calls. As such a mixed methods research approach was deemed suitable for the purpose of the study. Quantitative data collection and analysis was used to examine relationships and qualitative data collection and analysis was then used to further enhance the quantitative findings. In doing so integrative correspondence was achieved in this study by following the study's purpose throughout the research design, data collection and data analysis. Inference transferability refers to degree to which meta-inferences can be transferred to other contexts or settings. As the data for this study was collected from two countries and amongst varying types of participants the meta-inferences are deemed applicable to a broad range of users and further studies.

Table 5.2 and 5.3 contains the main findings from the integrated quantitative and qualitative data in both countries. The results for the hyposthesised relationships are outlined along with key insights from the qualitative interviews. Irish data is presented first followed by American data. Meta-inferences from these findings are presented afterwards.

5.4.1 Integrated Findings - Ireland

		Integrated Findings - Ireland		
Relationship	**Quantitative Findings**	**Qualitative Findings**	**Integration**	**Conclusion**
Privacy Risk Beliefs → THP(-)	✓	Privacy risks are acknowledged by participants, but they do little to deter trusting behaviours	Complementary	Quant. Findings: risk beliefs reduce THP. Qual. Findings: participants acknowledge risks and continue to share health data despite knowledge of risk, often to gain benefits.
Privacy Risk Beliefs → HIPC	✓	Participants indicated that privacy risk beliefs can play a low role in their HIPC. According to participants' risk is considered directly proportional to an individual's online safety competence.	Complementary	Qual. findings support quant. findings; the knowledge of risk can increase ones HIPC. Competent users may avoid risk.
Perceived Reciprocity → THP	✓	Participants indicated that levels of reciprocity can grow and are dependent on several subjective factors relating to personality, platform and purpose. When online communities are trusted and familiar, reciprocity appears more likely to occur	Complementary	Qual. findings show that reciprocity can increase based on personality, platform and purpose.

Perceived Reciprocity → HIPC (-)	X	Perceived reciprocity do not appear to play any role in HIPC	Convergence	Quant. and qual. findings both reveal no relationship between reciprocity and HIPC.
Social Influence → THP	X	According to participants Health professionals, family and close friends can heavily influence one's likelihood use a health platform and to therefore disclose personal health information within trusted communities.	Dissonance	Quant. findings found no significant relationship between Social Influence and THP. Qual. findings show participants are strongly influenced by social influence.
Social Influence → HIPC (-)	X	Participants made no reference to social influence having any impact on HIPC.	Convergence	Quant. and qual. findings both reveal no relationship between Social Influence and HIPC
HIPC → THP (-)	✓	Participants all express concern for their health data and a lack of trust in health technology vendors yet they all continue to self –disclose. Especially in cases of acute illness.	Complementary	Quant. findings show HIPC reduces THP. Qual. findings shows a complex relationship HIPC reduces THP but certain factors can positively impact trusting behaviours.
HIPC → SD (-)	X	Participants all express concern for their health data and a lack of trust in health technology vendors yet they all continue to self –disclose.	Dissonance	Quant. findings found no significant relationship between HIPC and SD Qual. findings shows a complex relationship. Qual. findings indicate HIPC might reduce SD but certain factors can

				positively impact disclosure behaviours.
THP → SD	✓	The link between online self-disclosure and trust is dependent on the one's trusting habits and the quality of a health platform. A trusting nature combined with trustworthy platforms leads to usage of these platforms and as a consequence users' self-disclosure of personal health information. Automated DHPs encourage subconscious SD.	Complementary	Quant. findings show THP increases SD. Qual. findings shows a complex relationship. THP increases SD especially when an individual is trusting in nature and when using favourable platforms. Automated DHPs encourage subconscious SD.
AGREE → SD	X	No strong link found between AGREE and SD	Convergence	Quant. and qual. found no link with AGREE
CONSCI. → SD (-)	X	Link found between CONSCI. and SD. The presence of conscientiousness can reduce one's propensity to self-disclose personal health information online, causing one to be risk aversive.	Dissonance	Quant. findings found no significant relationship between CONSCI. and SD. Qual. findings show participants who are high in CONSCI. are more likely to be cautious when disclosing health information online.
OPEN → SD	X	Some link found between OPEN and SD. Presence of OPEN could lead to greater SD.	Dissonance	Quant. findings found no significant relationship between OPEN. and SD. Qual. findings show participants who are high

				in OPEN. are more likely to SD.
EXTRO. → SD	X	Link found between EXTRO. and SD. The greater the presence of extroversion in a participant the more likely they are to self-disclose personal health information online.	Dissonance	Quant. findings found no significant relationship between EXTRO. and SD. Qual. findings show participants who are high in EXTRO. are more likely to SD.
NEURO. → SD (+)	✓	No link found between NEURO. and SD due to lack of presence of NEURO. in participants	Dissonance	Quant. findings show NEURO. can increase SD. This was not found in Qual. findings due to lack of NEURO. participants.

Table 5.2 Integrated Findings - Ireland

Note: ✓Supported, X not supported.

5.4.2 Integrated Findings – United States

		Integrated Findings – United States		
Relationship	**Quantitative Findings**	**Qualitative Findings**	**Integration**	**Conclusion**
Privacy Risk Beliefs → THP(-)	✓	Privacy risks are acknowledged by participants but they do little to deter trusting behaviours	Complementary	Quant. Findings: risk beliefs reduce THP. Qual. Findings: participants might continue to share data despite knowledge of risk in some cases.
Privacy Risk Beliefs → HIPC	✓	Participants indicated that privacy risk beliefs can play a low role in their HIPC. According to participants' risk is considered directly proportional to an individual's online safety competence.	Complementary	Qual. findings support quant. findings the knowledge of risk can increase ones HIPC. Competent users may avoid risk.
Perceived Reciprocity → THP	✓	Participants indicated that levels of reciprocity can grow when family or close friends are the information receivers. Participants regard reciprocity as an individual choice without an obligation.	Complementary	Qual. findings show that reciprocity can increase based on audience. No obligation to reciprocate.
Perceived Reciprocity → HIPC (-)	X	Privacy concerns do not appear to play any role in HIPC.	Convergence	Quant. and qual. findings both reveal no

				relationship between reciprocity and HIPC.
Social Influence → THP	✓	According to participants Health professionals, family and close friends can influence one's likelihood use a health platform and to therefore disclose personal health information within trusted communities.	Convergence	Quant. findings show significant relationship between Social Influence and THP. Qual. findings show participants are strongly influenced by social influence.
Social Influence → HIPC (-)	X	Participants made no reference to social influence having any impact on HIPC.	Convergence	Quant. and qual. findings both reveal no relationship between Social Influence and HIPC
HIPC → THP (-)	✓	Participants all express concern for their health data and a lack of trust in health technology vendors yet they all continue to self –disclose. Especially in cases of acute illness. Participants are overwhelmed by the steps required to secure their data and are concerned with future threats to their data.	Complementary	Quant. findings show HIPC reduces THP. Qual. findings shows a complex relationship, HIPC reduces THP but certain factors can positively impact trusting behaviours. Participants find it difficult to protect data. Future concerns are evident.
HIPC → SD (-)	X	Participants all express concern for their health data and a lack of trust in health technology vendors yet they all continue to self –disclose.	Dissonance	Quant. findings found no significant relationship between HIPC and SD Qual. findings shows a complex relationship. Qual. findings indicate

				HIPC might reduce SD but certain factors can positively impact disclosure behaviours.
THP → SD	✓	The link between online self-disclosure and trust is dependent on the one's trusting habits and the quality of a health platform. A trusting nature combined with trustworthy platforms leads to usage of these platforms and as a consequence users' self-disclosure of personal health information. Automated DHPs encourage subconscious SD.	Complementary	Quant. findings show THP significantly increases SD. Qual. findings shows a complex relationship. THP increases SD especially when an individual is trusting in nature and familiar with THP. Automated DHPs encourage subconscious SD.
AGREE. → SD	X	Link found between AGREE. and SD. The greater the presence of agreeableness in a person the more likely they are to feel safe when they self-disclose personal health information online.	Dissonance	Quant. findings found no significant relationship between AGREE. and SD. Qual. findings show participants who are high in AGREE. feel comfortable disclosing in familiar THPs.
CONSCI. → SD (-)	✓	Link found between CONSCI. and SD. The presence of conscientiousness can reduce one's propensity to self-disclose personal	Complementary	Quant. findings strong significant relationship between CONSCI. and SD. Qual. findings show participants who are high in CONSCI. are more

		health information online, causing one to be risk aversive.		likely to be cautious when disclosing health information online.
OPEN. → SD	X	Some link found between OPEN and SD. Presence of OPEN could lead to greater SD.	Dissonance	Quant. findings found no significant relationship between OPEN. and SD. Qual. findings show participants who are high in OPEN. are more likely to SD.
EXTRO. → SD	✓	Link found between EXTRO. and SD. The greater the presence of extroversion in a participant the more likely they are to self-disclose personal health information online.	Complementary	Quant. findings found significant relationship between EXTRO. and SD. Qual. findings show participants who are high in EXTRO. are more likely to SD.
NEURO. → SD (+)	X	No link found between NEURO. and SD due to lack of presence of NEURO. in participants	Complementary	Quant. findings show NEURO. no link to SD. This was not found in Qual. findings due to lack of NEURO. participants.

Table 5.3 Integrated Findings - U.S.

Note: ✓Supported, X not supported.

5.4.3 Development of Meta-Inferences

A number of meta-inferences have been drawn from the integrated findings. These meta-inferences have been developed by combining inferences found in both countries in order to strengthen the transferability and generalizability of the meta-inferences that have been developed (Venkatesh, Brown and Bala, 2013). The first meta-inference relates to privacy management and provides support for communication privacy management (CPM) theory: as individual's express digital competence they are more willing to disclose personal health information. The second meta-inference relates to THP and provides support for social exchange theory (SET): individuals are willing to disclose personal health information in return of tangible and intangible health and wellness benefits. The third meta-inference pertains to HIPC and THP and provides support for social penetration theory (SPT): under certain conditions individuals are willing to reciprocate deeper disclosures of personal health information, however if a privacy risk is observed individuals are also willing to withdraw from a disclosure exchange. A forth meta-inference relates to HIPC and supports SPT. When individuals believe disclosure of personal health information could benefit public health they are willing to reduce their HIPC. The fifth meta-inference relates to personality and supports SPT. Individuals ranking high in extroversion are more willing to self-disclose, while individuals ranking high in conscientiousness may reduce their disclosures.

The final meta-inference is drawn from a narrative present in both Irish and American data and relates to self-disclosure. Individuals using automated DHPs are often unware of their self-disclosures. Due to the nature of health technologies individuals may subconsciously disclose personal health information, as a result of using a wearable device. The meta-inferences are summarised in table 5.4

	Meta-inference	**Supporting Constructs**
1.	*Digital skills competence can increase disclosure of personal health information.*	Privacy Risk Beliefs Health Information Privacy Concerns
2.	*Tangible and intangible health and wellness benefits can increase disclosure of personal health information.*	Trust in Health Platforms
3.	*Social influence, quality information, reputation and design can increase deeper disclosures of personal health information, however if privacy risks are observed disclosure behaviours may decrease.*	Trust in Health Platforms Health Information Privacy Concerns
4.	*Perceived benefits to public health can reduce HIPC.*	Health Information Privacy Concerns
5.	*Extroversion can increase self-disclosure, conscientiousness can reduce self-disclosure.*	Personality
6.	*Automated DHPs can subconsciously influence disclosure of personal health information.*	Self-Disclosure Trust in Health Platforms

Table 5.4 Meta-inferences

5.5 Conclusion

This chapter presented the findings from 20 qualitative interviews from Ireland and the United States. The methods for analysing the data were outlined as were the steps taken for data validation. The qualitative findings were then discussed. Quantitative and qualitative findings were then integrated. The following chapter will discuss these findings along with their theoretical and practical implications.

6 Chapter Six: Discussion

6.1 Introduction

This study examines that factors that influence user self-disclosure of personal health information on digital health platforms. This chapter revisits the core objectives of the study and discusses how the integrated quantitative and qualitative findings meet these objectives and answers the related research questions. The chapter beings with an outline of the research objectives that were first presented in chapter One. The key findings of the research and their implications, specifically the theoretical contributions of the research to the body of knowledge, are then discussed. A revised framework for understanding the factors that influence user self-disclosure of personal health information on digital health platforms is then presented. Following this, the implications of the research findings for practitioners are outlined. The chapter concludes with an overview of the contributions of this research with regard to empirical findings, theory, context, method and practical implications. The chapter structure is depicted in figure 6.1 below.

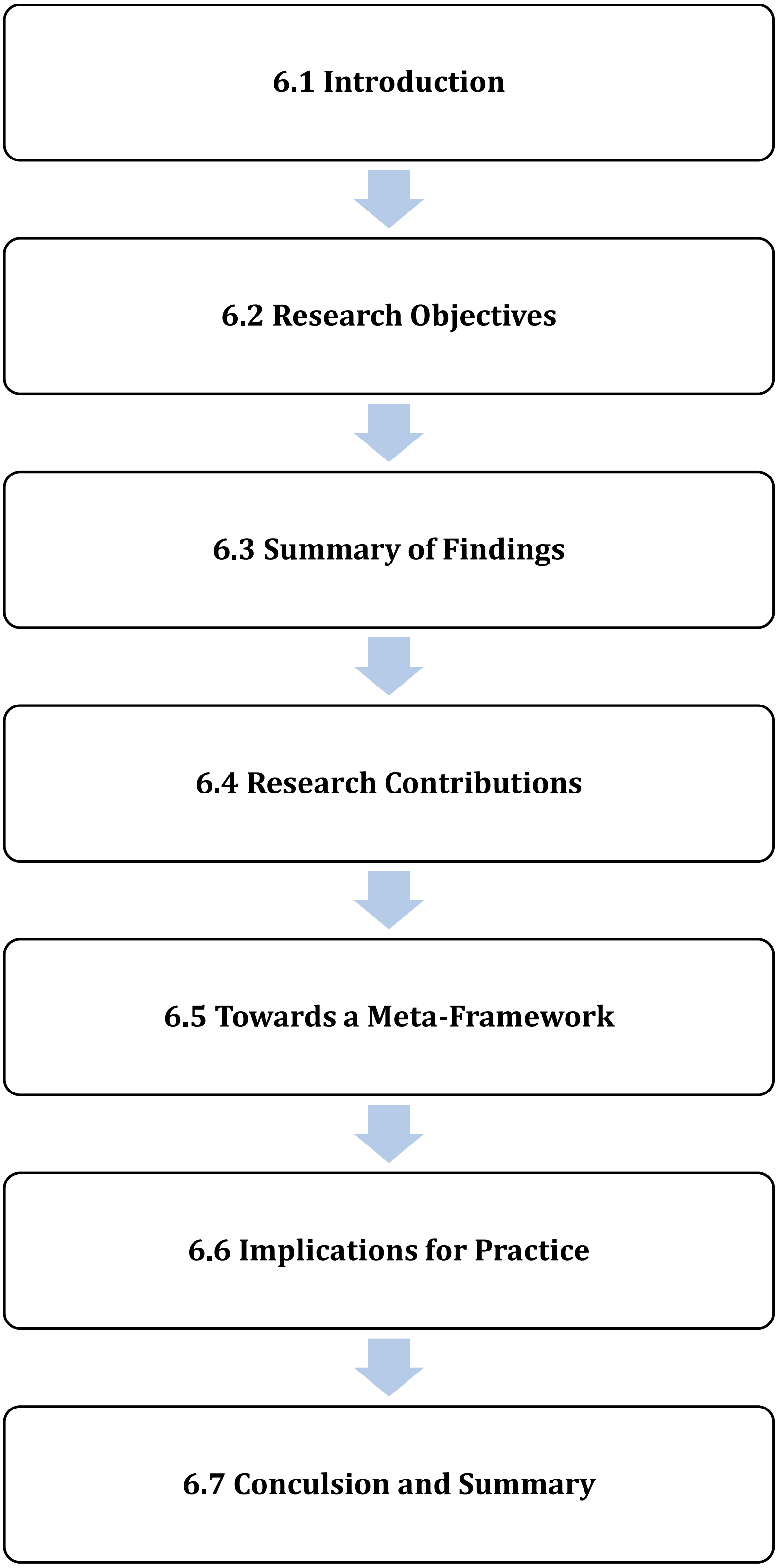


Figure 6.1 Chapter Structure

6.2 Research objectives

This research examines user self-disclosure of personal health information on digital health platforms. It proposes that online self-disclosure in this context is influenced by two distinctly different and important factors, namely the individual's level of trust in health platforms (THP) and by their health information privacy concerns (HIPC), both of which are shaped by antecedent factors. These shape the extent of the self-disclosure response. It also proposes that the formation of these trust beliefs and privacy concerns can vary across different cultures and the self-disclosure response can be influenced by a number of personality traits.

Following a review of extant literature, a number of gaps in our current understanding of the factors that shape online self-disclosure of health information were identified. Much of these relate to what generates self-disclosure in the context of health information on DHPs. Moreover, that review also showed that there is a need to elucidate the relationship between HIPC and THP, the direction of this relationship and the drivers of this relationship in more detail than has been available to date.

A review of IS literature was undertaken which yielded important insights which contributed to the development of a novel framework for this study. Using data gathered in Ireland and the U.S., this study develops a framework that harnesses social exchange theory (SET) and social penetration theory (SPT) as a lens to understand online self-disclosure of personal health information. It does this by drawing on extant literature to provide a more granular examination of the factors that generate THP and HIPC. It then examines the influence of THP and HIPC on online self-disclosure. Finally, the study offers a unique look at the role of personality traits and the influence they have on one's likelihood to self-disclose health information online. This research focus on personality traits was influenced by a growing number of studies that have revealed personality traits to have significant roles in online disclosure behaviour (Xi Chen, Pan and Guo, 2016; Kim, 2018), moreover researchers in online health have called for the inclusion of personality traits in future studies about online self-disclosure (Bansal, Zahedi and Gefen, 2010; Nguyen, Bin and Campbell, 2012).

A two-stage mixed-methods data collection approach was employed to explore these propositions. Data from Irish and American citizens was collected, providing unique and valuable insights. The study of Irish citizen data as it relates to health information disclosures is at a nascent stage, while the same body of research is at a mature stage in America. First, a quantitative survey was used to collect data from participants in Ireland and America. This provided empirical insight into the construct relationships. Following this, qualitative research interviews were conducted with Irish and American participants in order to develop deeper understandings of those relationships. The quantitative and qualitative findings were subsequently integrated and evaluated in the context of the hypothesised relationships. The research had five core objectives which are described in the following sections.

6.2.1 Examining the Antecedents of Self Disclosure on Digital Health Platforms

The overarching research objective of this research is to examine the antecedents of self-disclosure of health information in a digital health platform context. Based on a review of extant literature about self-disclosure in online contexts, a number of key constructs emerged, specifically trust and information privacy concerns, with the latter frequently referred to as risk beliefs in the literature. A number of other influential factors, specifically social influence and reciprocity, were also identified as relating to self-disclosure, trust beliefs and information privacy concern outcomes in a variety of contexts.

The literature revealed self-disclosure to be a complex construct (Kim, 2014) and one that is shaped by context. For example, in their systematic review of online self-disclosure Nguyen, Bin and Campbell, (2012) revealed self-disclosure to have dynamic antecedents that can alter based on context and modes of communication. This becomes even more evident with disclosure of sensitive health information in an online context, which may have particularly consequential outcomes for the individual (Yuchao, Ying and Liao, 2021). Extant literature therefore indicated a more granular approach was necessary for our understanding of how these antecedents function in a digital health context and how they would assist in a more thorough realisation of the overall research objective (Bansal, Zahedi and Gefen, 2010; Posey *et al.*, 2010; Xu, Le and Montague, 2014; Kim, 2016).

Previous research has treated the relationship between online self-disclosure and it’s antecedents in a linear fashion (Posey *et al.*, 2010) however this fails to capture the sensitive and consequential nature of personal health information when disclosed in an online context. For this reason, the present study chose to draw more comprehensively from IS literature in order to produce a 2nd order construct model that reflects the sensitive nature of citizen informational self-disclosures on DHPs and their awareness of the potential for consequential outcomes arising from such disclosure. This included a focus on two main drivers of self-disclosure on DHPs, specifically trust in health platforms (THP) and a more granular focus on information privacy concerns/ risk beliefs, namely health information privacy concerns (HIPC). In order to develop an enhanced understanding of health information disclosures, these two constructs were the subject of in depth analysis which also included a focus on the strength of their influence on self-disclosure, their inter-relationship and the factors potentially influencing their formation. This was complemented by acknowledgement and measurement of the role of differing personality factors on the individual's self-disclosure response in a DHP context, thereby providing far more detailed insights into the formation of self-disclosure responses in this unique and important context, than has previously been the case. The approach to analysis of THP and HIPC are discussed below.

6.2.2 Measuring Trust in Health Platforms

As noted, the disclosure of personal health information can be consequential and sensitive. Previous research (Joinson *et al.*, 2010; Sillence, Hardy and Briggs, 2013) has shown that trust is necessary in order for sensitive disclosures to occur. In a technology-mediated environment, trust assumes even greater importance, particularly in reducing perceptions of risk and enabling more confident interaction behaviour. Whilst this effect has been shown repeatedly in the ecommerce literature, far less attention has been paid examining trust in online health contexts. As such, a core focus of this research is trust formation and its influence on self-disclosure in an online health platform context. Previous research has employed a variety of factors to measure more general online trust (Kim, 2016). This has ranged from examinations in contexts including trust in social networks like Facebook (e.g. Lankton, Mcknight and Tripp, 2015), ecommerce platforms (e.g. Palvia, 2009, Connolly and Bannister, 2007; Gefen and Straub, 2000), workplace platforms (e.g Posey *et al.*, 2010), with a smaller number focusing on trust in health websites (e.g. Sillence *et al.*, 2011). This wide variety of examinations and study contexts has understandably led to difficulties in extrapolation of findings and their generalisation. Adding to the complexity is the fact that these studies tend to focus on adoption as the dependent variable, or (in the case of Connolly *et al.*, (2022) on how trust influences online engagement in health communities. As a consequence, how trust influences self-disclosure in an online context and more particularly in an online health context has remained undetermined. This is particularly surprising as DHPs are a particularly unique context due to the sensitive nature of health data and the risks associated with disclosures. Unsurprisingly, researchers such as Vega, Montague and DeHart, (2010; 2011) have highlighted the need to focus more specifically on the trust construct within the domain of health, specifically digital health platforms. This research therefore answers that call. In order to develop deeper examination into how trust in digital health platforms (THP) is formed, a number of sub-dimensions that have been shown to influence its formation were incorporated to provide a comprehensive, granular measure of trust for use in an online health context. To that end, a systematic review of online trust was conducted and four predominant dimensions were identified as being of particular relevance to the current study: design, information quality, reputation and perceived trust in technology vendors. The first three, design, information quality and reputation, were selected due to their application across a wide range of online trust research studies conducted across multiple contexts, all of which have repeatedly confirmed their importance (Walther, Wang and Loh, 2004; Sillence *et al.*, 2011; Kim, 2014). The fourth trust dimension is perceived trust in technology vendors (Song and Zahedi, 2007; Dinev *et al.*, 2016). This dimension was included as the unique context of DHPs requires that attention is paid to this specific context, moreover researchers have called for clarity on the role of technology vendors in trust development when in a health context (Dinev *et al.*, 2016) . This detailed measure of THP consists of four dimensions all of which were tested via quantitative surveys and qualitative interviews across two countries. As the literature has indicated that both social influence and reciprocity can influence formation of trusting behaviours (Vega, Montague and DeHart, 2010; Vega, Montague and Dehart, 2011; Tamjidyamcholo *et al.*, 2013; Sánchez-Franco and Roldán, 2015), these relationships and their potentially formative influence on trust in digital health platforms were also examined. Figure 6.2 below outlines the proposed measure for THP.

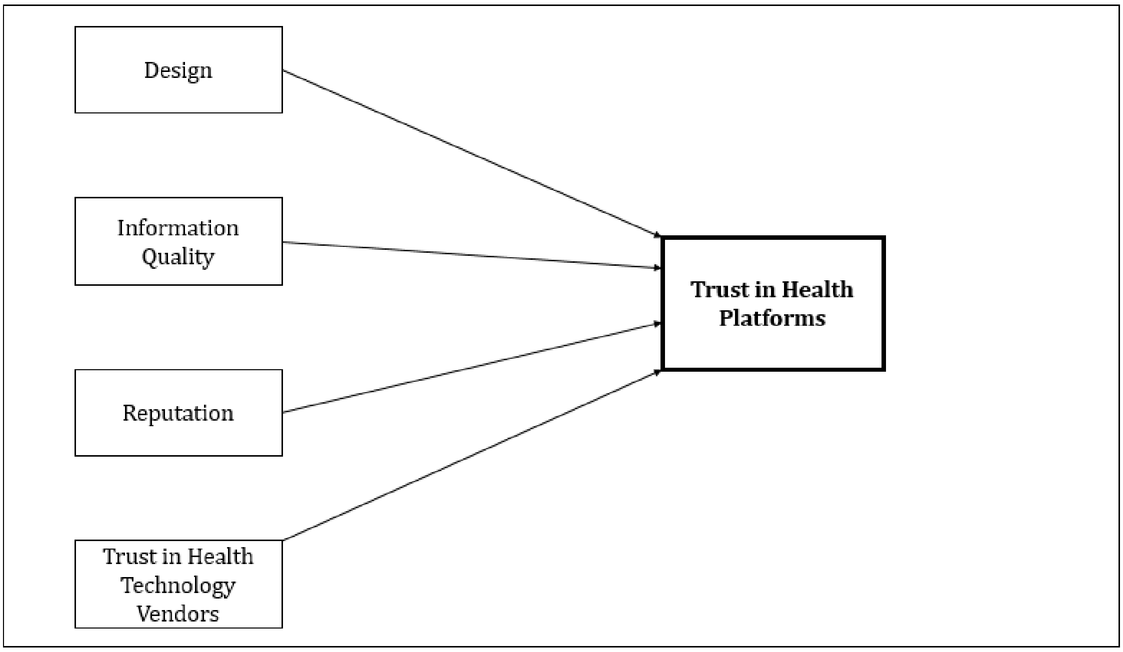


Figure 6.2 THP measure

6.2.3 Measuring Health Information Privacy Concerns

As noted, the literature has indicated information privacy concerns, and more specifically health information privacy concerns (HIPC) as a key factor influencing behavioural outcomes, including that of disclosure in offline contexts (Kimmel, 1996; Sheehan, 2002). Preliminary research indicates it also influences adoption behaviours, including e-health adoption (e.g. Fox and Connolly 2018). However, its role in driving online self-disclosure in relation to digital health platforms (and the factors influencing its formation) remains undetermined. In order to examine this potential influence in a DHP context, a suitable measure for HIPC was required. Previous research has utilised different measures when examining information privacy concern. These include the Concern for Information Privacy (CFIP) measure (H. Jeff Smith, Milberg and Burke, 1996) which was used to examine privacy concerns on an organisational information practice level and incorporated four common dimensions: Collection, Unauthorised Secondary Use, Improper Access and Errors. It also includes the Internet User's Information Privacy Concerns (IUIPC) measure (Malhotra, Kim and Agarwal, 2004) which was developed to understand individuals' concerns when using the internet and included collection, control and awareness in its dimensions. More recently, Hong and Thong, (2013) combined CFIP and IUIPC to produce the Internet Privacy Concern (IPC) measure. This comprehensive measure includes: Collection, Unauthorised Secondary Use, Improper Access, Control, Awareness and Errors. While the IPC measure has been utilised in generic online contexts (Hong and Thong, 2013), it has also been applied in an online health context, albeit to measure information privacy concerns in an electronic health record context (Fox and Connolly, 2018). Due to the comprehensive nature of this measure and its previous successful application to an online health context, it was deemed suitable for the present study and was extended to examine self-disclosure in a DHP context. This measure consists of six dimensions all of which were tested via quantitative surveys and qualitative interview across two countries. As the literature has indicated that both social influence and reciprocity has potential to influence information privacy concerns (Zhou and Li, 2014; Alaqra and Wästlund, 2019; Khalil, Zia and Abdallah, 2019; Fox *et al.*, 2021), the relationship of these factors to HIPC were also examined. The six dimensions are displayed below in figure 6.3.

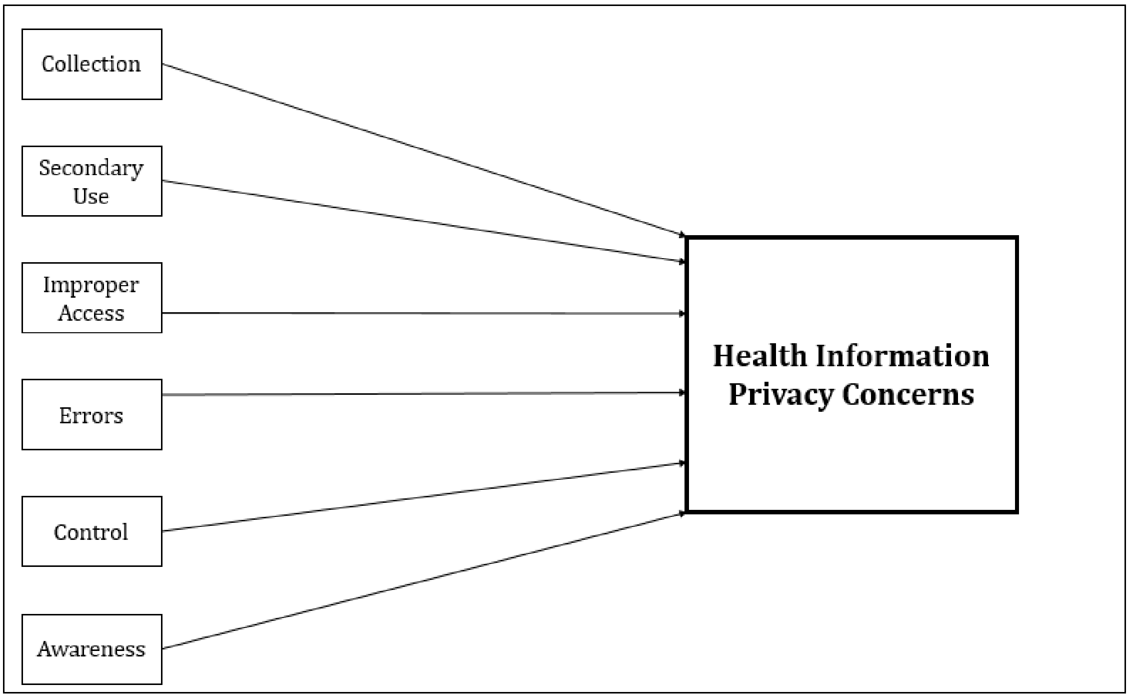


Figure 6.3 HIPC measure

6.2.4 Exploring the Relationship Between Personality Traits and Self-Disclosure

The final objective of this study was to develop an understanding of the potential influence of personality traits on self-disclosure, in a health context. Much research on self-disclosure in an online health information context ignores the potential distinctions between individuals and their personality traits this is despite previous IS research revealing that personality traits are deemed as having a considerable role to play in online behaviour in other contexts (Correa, Hinsley and de Zúñiga, 2010; Nadkarni and Hofmann, 2012), as such the role of personality traits in an online health context has not been comprehensively explored. Previous research has examined the role of personality traits in online disclosures in non-health information contexts (XI Chen, Pan and Guo, 2016; Chan, 2021). This literature around the topic of personality traits suggests that the traits of extroversion, neuroticism and conscientiousness may have a role to play in an individual's online self-disclosures however this assertion remains underexplored with regard to online self-disclosure of health data. A small but growing number of studies have attempted to explore the role of personality traits in an online health context (Bansal, Zahedi and Gefen, 2010; Nikbin, Iranmanesh and Foroughi, 2020; Badreddine, Blount and Quilter, 2022). Indeed, while Bansal, Zahedi and Gefen, (2010) included the examination of personality traits in their health context study, they chose to examine the relationship between personality traits and perceived health information sensitivity, while Badreddine, Blount and Quilter, (2022) focused on community interaction among cancer patients online. However, there remains a lack of understanding as to how personality traits potentially influence self-disclosure directly, therefore this present study extends the examination of personality traits to online health disclosures. To do this a novel and concise quantitative measure known as the Ten Item Personality Inventory (TIPI) (Gosling, Rentfrow and Swann, 2003) was used as it allows for a personality trait assessment to be conducted within a larger study, while follow up qualitative interviews were conducted to develop deeper understandings of personality traits for the study.

6.3 Summary of Findings:

The findings confirm the relationship between THP and self-disclosure. Its formation is shaped by a number of factors. Firstly, both risk beliefs, and more specifically HIPC, exert a significant negative influences on trust, as is to be expected. Secondly, it is positively influenced by reciprocity. However, the relationship between social influence and trust, while positive, is not significant for the Irish sample, whilst it is significant for the USA sample. Conscientiousness and extroversion also play significant roles in influencing self-disclosure on a DHP. The level of influence of each of these antecedents differed in the two countries examined. The following section reviews key findings and variations from both Ireland and the United States.

Trust in Digital Health Platforms

6.3.1 THP and Self-Disclosure

The study confirms a positive influence of THP on self-disclosure. This finding was found in both countries. This relational support was found in previous studies albeit in a non-health information context (Joinson *et al.*, 2010; Posey *et al.*, 2010; Shih, Lai and Cheng, 2017). Interviews echoed these findings, in particular they noted that a trustworthy design in platforms can lead to usage of these platforms and as a consequence citizens' self-disclosure of personal health information. These findings advance our understanding of the influence THP has on self-disclosure, particularly in a health context.

6.3.2 HIPC and THP

With regard to HIPC and THP the findings confirm a significant negative relationship between HIPC and THP, in both countries. Previous research into the relationship between HIPC and trust has offered conflicting results with some finding no significant relationship (Bansal, Zahedi and Gefen, 2010; Fox and Connolly, 2018) this is despite IS literature indicating a significant relationship (Taddei and Contena, 2013; Lowry, Dinev and Willison, 2017). Again the interviews offered further nuanced insight to the HIPC / THP relationship. While participants indicated that HIPC could reduce THP they also indicated that should their health information have perceived benefits to public health this could reduce their HIPC. These findings advance our understanding of the HIPC / THP relationship while also contributing to our knowledge on how HIPC might be reduced.

6.3.3 Privacy Risk Beliefs and THP

The findings confirm a negative influence of privacy risk beliefs on THP. This applies equally in both Ireland and the U.S. This supports findings from previous researchers in both commercial and online health research arenas (Bansal, Zahedi and Gefen, 2010; Posey *et al.*, 2010; Fox and James, 2020) who found that perceived risk beliefs can reduce one's trust in digital platforms. The interviews also revealed support for the negative influence of perceived risk beliefs on THP in both countries. In summary it is argued the perceived risk beliefs can decrease THP.

6.3.4 Perceived Reciprocity and THP

The findings confirm the positive influence of perceived reciprocity on THP. This applies equally in the context of Ireland and the U.S. This echoes the findings of previous researchers that looked at the role of reciprocity in non-health information online platforms (Posey and Ellis, 2007; Posey *et al.*, 2010) and confirms that perceived reciprocity exerts an important influence on the formation on trust in an online health information context. Furthermore, these findings reveal the relationship between perceived reciprocity and trust in an online health information context extends beyond cultural boundaries. Additionally, the interviews also found perceived reciprocity to exert a strong influence in THP. The interviews further revealed that participants' THP was likely to increase when family and close friends are perceived to reciprocate personal disclosures of health information.

6.3.5 Social Influence and THP

The findings confirm a positive relationship between social influence and THP. This finding was found in the U.S. data, however this relationship was not present in Irish quantitative data, thus offering an insight into possible cultural differences. Previous research and literature has found a positive relationship between social influence and trust in online platforms however this study confirms that the relationship exists in an online health context (Posey *et al.*, 2010; Desjarlais *et al.*, 2015; Shih, Lai and Cheng, 2017). Of note, the interviewees from both countries found social influence to have a positive relationship with THP, with participants from both countries indicating that social influence from peers can increase their THP, thus indicting a mild social influence amongst Irish participants.

Health Information Privacy Concerns

6.3.6 HIPC and Self Disclosure

The findings show that HIPC does not influence self-disclosure in a DHP context. Its effect occurs through its impact on trust and the influence of the latter construct on self-disclosure. This finding was consistent across both countries and represents a particularly important finding of this research.

6.3.7 Privacy Risk Beliefs and HIPC

The findings confirm a positive relationship between perceived risk beliefs and HIPC in both countries. While research on this relationship is at a nascent stage previous studies also find support for this positive relationship (Fox and Connolly, 2018; Fox and James, 2020). The findings from this study indicate that privacy risk beliefs can increase HIPC. However, the interviews from both countries in this study offer more nuanced insight as participants indicted that while perceived risk beliefs can increase HIPC, digital skill competence has potential to reduce HIPC.

- Personality Traits and Self-Disclosure

The role of personality traits and their influence on one's likelihood to self-disclose in a health context was also examined. The study provided quantitative support for the positive influence of neuroticism on self-disclosure in Irish data. This relationship was not found in U.S. data. The study provided quantitative support for the negative influence of conscientiousness on self-disclosure in U.S. data. This relationship was not found in Irish data. Furthermore, quantitative U.S. data found extroversion to have a positive influence on self-disclosure. This relationship was not found in Irish data. These quantitative findings are in agreement with previous studies relating to personality traits and online self-disclosure behaviours (Chen, Pan and Guo, 2016) however this study extends our understanding to an online health information context. The interviews offered a deeper understanding of the role of personality traits, specifically both extroversion and conscientiousness where in fact present among Irish and U.S. participants. Participants indicated that extroversion could increase disclosure behaviour while conscientiousness could reduce disclosure behaviour. In summary, it is argued that in both countries the greater the presence of extroversion in a person the more likely they are to self-disclose, while the greater the presence of conscientiousness in a person the more likely they are to not self-disclose. These findings extend our understanding of personality trait influence on self-disclosure to a health context.

6.4 Research Contributions

This study makes a number of key contributions to I.S. literature in relation to the factors that influence user self-disclosure of personal health information on digital health platforms. The following section presents these contributions.

The first contribution relates to our understanding of the factors that drive online self-disclosure in a health information context. This study provides timely and valuable insights to self-disclosure antecedents in a digital health context, which has assumed increasing importance in a post pandemic world. In doing so, it has answered calls for further examination of self-disclosure in different CMC contexts and for the extension of theoretical lenses to new contexts, namely SET and SPT (Nguyen, Bin and Campbell, 2012). Many studies have attempted to understand the antecedents of self-disclosure in online commercial and social environments (Posey and Ellis, 2007; Joinson *et al.*, 2010; Posey *et al.*, 2010). However, with the advent of the Covid-19 pandemic the world has changed. Citizen exposure to DHPs has increased, while health systems struggle with staff and resource shortages. With this new exposure to DHPs comes an increased necessity to understand self-disclosure in a health context rather than a commercial context. For example, not all exposures to DHPs during the pandemic have been successful, this is due to a number of issues mainly poor design, data governance and rollout strategies (Marabelli, Vaast and Li, 2021; Ghose *et al.*, 2022; Köngeter *et al.*, 2022). Despite this, with guided exposure to well designed, user friendly DHPs there is an opportunity to alleviate some of the economic burden that currently rests on health systems. Indeed, researchers have shown that successful rollout of user centric DHPs can increase the likelihood of citizen uptake in Telehealth (Ghose *et al.*, 2022), thus helping to reduce the burden on health systems. If this opportunity is to be realised however, it is imperative to develop our understanding as to what drives user disclosures on DHPs, as without disclosures these DHPs are rendered useless. To this end the current study makes a valuable contribution on the matter. That is to say, this study has extended previously examined antecedents such as social influence, perceived reciprocity and privacy risk beliefs (Posey *et al.*, 2010) to a health context. In addition, this study has introduced factors previously underexplored in this context, such as personality traits, THPs and HIPCs. The outcome is a contemporary framework that extends SET and SPT to an online health context which can be utilised to understand what drives online self-disclosure of consequential health information.

The second research contribution of this study relates to the specific role of trust in DHPs and the influence it has on user self-disclosure of health information online. While recent research has examined the role of trust in commercial online disclosures (Posey and Ellis, 2007; Joinson *et al.*, 2010; Posey *et al.*, 2010; Nguyen, Bin and Campbell, 2012; Shih, Lai and Cheng, 2017), research into the role of trust as it relates to online self-disclosures of personal health information is still underexplored, despite Bansal, Mariam and Gefen, (2016) showing that context can impact trusting behaviours. This study bridges that gap in our knowledge, responding to calls for a deeper exploration of what drives trust in health platforms (Vega, Montague and DeHart, 2010; Vega, Montague and Dehart, 2011; Kim, 2016). It reveals trust to have a direct relationship with disclosure of health information on DHPs, be it a wearable device, app or online community – and in fact to have a more significant influence on such disclosure than the individual's health information privacy concerns. This adds significantly to the body of knowledge, showing that not only is trust a key factor in user adoption of health websites (Sillence *et al.*, 2004; Vega, Montague and DeHart, 2010), but that it is the most important factor in relation to self-disclosure in a digital health platform context. An associated contribution relates to how this examination of trust was undertaken - by decomposing the trust construct to examine relevant trust dimensions and their effect – and in doing so, responding to calls to employ new measures for online trust in health platforms (Adjekum, Blasimme and Vayena, 2018). The results confirm that THP is generated by platform design, information quality, reputation and trust in health technology vendors. The interviews further reveal trust in health technology vendors as the trust dimension exerting the greatest influence on THP. As such this study offers important identification and insight into the dimensions of trust which motivate user disclosures of health information on digital platforms. It confirms not only that THP has constituent layers, but that it is the most influential driver of health disclosures on DHPs.

The third research contribution of this study relates to the role of privacy risk beliefs and of HIPC in relation to self-disclosure behaviour. Much research has indicated that risk beliefs and HIPC influence adoption outcomes, including in relation to e-health adoption (Fox and Connolly, 2018). Similarly, there is plentiful research confirming the negative relationship between privacy concerns and self-disclosure in both traditional and online contexts (e.g. Kimmel, 1996; Sheehan, 2002; Bansal, Zahedi and Gefen, 2010; Posey *et al.*, 2010). Surprisingly little research exists in relation to health information privacy concerns and their effect on disclosure behaviour of personal health information in the context of digital health platforms. However, recent research by Chua, Ooi and Herbland, (2021) examining the effects of different personal data categories - one of which was health data - on Malaysian user's information privacy concerns and online disclosure behaviour, found significantly different levels of perceived disclosure intention and information privacy concern associated with different personal data categories. They found that authenticating and financial categories posed a far higher level of information privacy concern, than was the case for medical/ health information, while having the lowest level of disclosure intention. In fact, information privacy concerns regarding medical / health information were not a priority concern among the sample and did not exert a strong restraining effect on disclosure intention. Questioning the culture independence of this finding, the authors have called for research using different demographics from other countries and samples, and for additional factors to be tested, as perceived privacy and disclosure intention are contextually driven (Sheehan, 1999; Albrechtsen, 2007; Chua, Ooi and Herbland, 2021). The current research therefore adds to a small but growing body of research (including the social network research of Taddei and Contena, 2013) which shows that information privacy concerns and their influence on disclosure behaviour are contextually driven and as a consequence its effect should not be assumed, and that its expression follows a more complex effect pathway than previously thought, as discussed in the next contribution.

The fourth research contribution of this study relates to the relationship between privacy and trust and how both of these work together to influence disclosure of health information. This contribution elucidates the nature of this relationship by examining how these duel factors interact to shape self-disclosure of health information online. First, the research confirms that the relationship between both constructs exists in an online digital health platform context, but as previously noted, it also reveals HIPC to only have an indirect relationship with online self-disclosure of health information. As noted, this finding is supported by Taddei and Contena, (2013) who found that trust and control had a central role in influencing online self-disclosures on social networks and that privacy concerns did not have a direct relationship with online self-disclosure. One explanation may be that of increased generational familiarity with online platforms resulting in users being more aware of inherent privacy risks, but confident in their evaluation of web vendors, their design competence indicators and reputation. Future vendors could exploit this finding by consulting with research undertaken to enhance user awareness of online trust and risk indicators on digital platforms via privacy by design principles and explainability by design principles, both of which are emerging trends in automated digital systems research (Perera *et al.*, 2016; Abeywickrama *et al.*, 2022). The findings of the current research build on the work of Posey *et al.,* (2010) which indicated a positive relationship between trust beliefs and disclosure in a workplace online community, but deepens that insight by showing the precise pathway and behavioral expression of that trust response, as well as the limits of this relationship in an DHP context.

A related contribution is that the study findings reveal the direction of the relationship between HIPC and THP, that is that HIPC negatively influences THP, which in turn can reduce disclosure behaviours. This is in contrast to previous research which found trust to influence HIPC. For example, in their research on mHealth adoption intentions Fox and Connolly, (2018), found trust to directly influence HIPC. However this present research reveals that when the outcome variable is self-disclosure of health information the opposite relationship applies. This contrasting finding could be due to health related behaviours having different motivators than health related intentions (Faries, 2016). In this present research for example THP appears as a trigger for disclosure behaviour while Fox and Connolly, (2018), found HIPC to be a trigger for intention. Indeed, this finding is of particular signifcance as intention can be a poorer predictor of actual health behaviour change (Faries, 2016), suggesting that greater adherence to THP by health technology vendors and policy makers could potenitally increase disclosures of health information online and positive health outcomes.

The fifth contribution of this research relates to the role of perceived reciprocity in trust development. Previous research has shown perceived reciprocity to have an influential role in self-disclosure, albeit in an online commercial context (Posey *et al.*, 2010). Indeed, much research links reciprocity with trust and self-disclosure, in that when an environment is perceived to be low in risk deeper revelations occur and as reciprocation of revelation is experienced the intimacy of these revelations also grows in amount and depth (Posey and Ellis, 2007; Posey *et al.*, 2010; Tamir and Mitchell, 2012; Bansal and Gefen, 2015). This study has extended the understanding of perceived reciprocity to an online health context and repositioned the understanding of its directional relationship. Where Posey *et al.*, (2010) revealed perceived reciprocity to have a direct, linear relationship with self-disclosure, the present study shows perceived reciprocity to have a mediated relationship with self-disclosure. That is to say that perceived reciprocity has a significant influence on THP generation, which in turn influences disclosures of health information. While a few studies have found relationships between reciprocity and privacy concerns in online contexts, mainly on social networks (Alaqra and Wästlund, 2019; Khalil, Zia and Abdallah, 2019) this present research did not reveal a relationship. This contribution indicates reciprocity is a key factor in developing trust and subsequently disclosures. This relationship was confirmed in both Irish and USA samples.

The sixth research contribution of this study relates to the role of social influence in trust development. Previous research has shown social influence to have an significant role in generating self-disclosures in an online commercial context (Posey *et al.*, 2010). Shih, Lai and Cheng, (2017) have shown digital consumers to be subject to social influence by way of building dependency within an online group and that this in turn led to trust formation.

The current study has extended the understanding of social influence to an online health context and repositioned its directional relationship. Social influence in the present study is shown to have a significant influence on THP generation, which in turn influences disclosures of health information Based on extant literature, this study proposed that social influence would have a significant role to play in trust development. The findings confirm this to some degree. However, the findings revealed social influence to have greater significance in relation to the U.S. sample, in contrast to the Irish sample, thus indicating that social influence is not culture independent with regard to THPs and requires more attention than previously thought. This cultural difference could be a result of American citizens having greater exposure to DHPs than compared to Irish citizens and that this increased familiarity with DHPs could induce greater willingness to adhere to the experience of peers when considering whether trust DHPs and disclose health information (Bernstein, 2021).

The seventh research contribution of this study relates to the role of personality traits in user self-disclosure of health information online. Previous research has shown personality traits to influence self-disclosures in non-health contexts, such as social networks (Barnett *et al.*, 2015; XI Chen, Pan and Guo, 2016; Kim, 2018), with extroversion being particularly strongly associated with higher levels of self-disclosure. However, earlier research in a USA health context, examining the relationship between personality traits, perceived health information sensitivity and subsequent disclosure behaviour (Bansal, Zahedi and Gefen, 2010) found only a mild indirect connection between agreeableness and reduced self-disclosure. In contrast, the current research has shown that personality traits can positively and negatively influence the likelihood of disclosures of personal health information on DHPs. First, the trait of extroversion was shown to be associated with increased health disclosure behaviours, thus acting as a proxy for risk propensity as this trait is associated with being open to risk and willing to exchange experiences (McCrae and Costa, 1997; XI Chen, Pan and Guo, 2016). This finding was significant in U.S. quantitative data, but not in Irish quantitative data, indicating a possible cultural distinction. Second, the trait of conscientiousness was found to be associated with decreased health disclosure behaviours, thus acting as a proxy for risk aversion as this trait is associated with caution and risk averse tendencies (McCrae and Costa, 1997; XI Chen, Pan and Guo, 2016). Again, this finding was prevalent in U.S. quantitative data but not Irish quantitative data. Third, the trait of neuroticism was shown to be associated with increased health disclosure behaviours, thus acting as a proxy for anxiety and irrationality as this trait is associated with being easily influenced, often through fear (McCrae and Costa, 1997; XI Chen, Pan and Guo, 2016). This finding was prevalent in Irish quantitative data but not U.S. quantitative data. These findings reveal that the traits of extroversion, conscientiousness and neuroticism can influence one's disclosure behaviours in a health context and that their influence is not culture independent. This confirms the importance of the many calls to examine the role of personality traits in different IS contexts (Bansal, Zahedi and Gefen, 2010; Bansal, Mariam and Gefen, 2016; Xi Chen, Pan and Guo, 2016) and provides particularly unique insight into the effect of personality variables, confirming the importance of their inclusion in IS research.

A further contribution of this study relates to context. The context of this study is significant as previous studies historically focused on offline self-disclosure environments (Jourard, 1971; Cozby, 1972; Altman and Taylor, 1973; Wheeless and Grotz, 1977) or on online self-disclosure environments that had a commercial, ecommerce or office/workplace nature (Posey and Ellis, 2007; Joinson *et al.*, 2010; Posey *et al.*, 2010; Nguyen, Bin and Campbell, 2012; Shih, Lai and Cheng, 2017). Only in more recent years has IS research focused on self-disclosure and privacy concerns in online health platforms (Fox and Connolly, 2018). In focusing on a personal health information context this study helps to answer calls for research into the factors that impact health information technology usage (Bansal, Zahedi and Gefen, 2010; Dinesen *et al.*, 2016; Lowry, Dinev and Willison, 2017). Moreover, this study was undertaken using a unique sample set. Performed as a comparative study between data from Irish and American users this research offers rare and valuable insights. The study of Irish user data as it relates to health information disclosures is at a nascent stage, while the same body of research is at a mature stage in America; an important factor for validation purposes within this study

(Venkatesh, Brown and Bala, 2013). The combination of Irish data and American data contributes to research calls into health information concerns in both a European context and a cross cultural context (Bansal, Zahedi and Gefen, 2010; Anderson, Agarwal and Anderson, 2011; Bélanger and Crossler, 2011; Dinesen *et al.*, 2016; Lowry, Dinev and Willison, 2017).

With regard to the cross cultural context, overall analysis shows that cultural independence cannot be assumed. The samples used in this study are drawn from English-speaking first world countries with many commonalities. However different results were obtained for both in relation to a number of important relationships including social influence, extroversion and neuroticism. This confirms the need for further research which moves beyond use of samples with explicitly different cultural dimensions, as is traditionally assumed (Hofstede, 2011). In effect, there is a need to move beyond the assumption that first world countries or English speaking countries will provide similar results. Utilizing samples that draw from nationally similar contexts or regions represents an important avenue of research that may provide insights into cultural or regional variation in antecedents of disclosure, for example in their research King, Brankovic and Gillard, (2012) found participants from different states in Australia to have different online health privacy concerns.

Post-hoc contribution.

The post-hoc tests revealed important insights that also provide a valuable contribution to the body of knowledge regarding information self-disclosure on DHPs.

First, the post-hoc tests show that age differences influence the weighting placed on factors which can shape the pathway to disclosure. For example, they show that two factors - perceived reciprocity and social influence - exert a stronger influence on HIPC for younger respondents, than is the case for older respondents. This may reflect the greater emphasis that younger individuals place on the opinions of their peers when evaluating information privacy concerns in a technology-mediated context (Alaqra and Wästlund, 2019), whilst older cohorts may have more confidence in their own privacy evaluations or be less privacy sensitive in this context. This insight into the effect of age in determining the importance of factors which have potential to influence self-disclosure of personal health information advances our understanding beyond the linear relationship between constructs and behaviour which some researchers (e.g. Posey *et al.*, 2010) have proposed as having exclusive explanatory power for understanding self-disclosure, which did not incorporate consideration of the effect of age on the effect of those constructs in shaping self-disclosure behaviours.

Second, individuals who had an undergraduate degree were compared with those who had not pursued further education having completed secondary school. This analysis showed that the path between HIPC and self-disclosure was significant, indicating that HIPC has a stronger influence on self-disclosure for those individuals with an undergraduate degree, than is the case for those without higher education levels. This finding is consistent with research showing that individuals with an undergraduate degree tend to be more aware of online privacy risks (Hwang *et al.*, 2012; Lee *et al.*, 2019). In contrast, Yuchao, Ying and Liao, (2021) did not find HIPC to have a significant influence on self-disclosure on an online health community when observing education levels.

Third, post-hoc tests examining the effect of Internet experience levels in relation to the factors that influence self-disclosure provide interesting insights that advance our understanding. These results show that the path between HIPC and Trust was significant, indicating that HIPC exerts a stronger effect on trust beliefs for long term users of the Internet, than is the case for those with less Internet Experience. This result is consistent with Laric, Pitta and Katsanis, (2009) who revealed older, experienced U.S. users to hold higher privacy concerns than those younger than them. This may reflect negative experiences which those with longer terms of internet usage are more likely to have. Similarly, the path between perceived reciprocity and trust was significant, indicating that perceived reciprocity exerts a stronger effect on trust beliefs for those with more than 10 years Internet experience, than is the case for those with less Internet Experience. Again, this reflects a greater emphasis or valuing of reciprocity by those with longer levels of Internet experience. This finding is consistent with research by Legido-Quigley, Mckee and Green, (2014) who found older people to place greater value on reciprocity in a health care context. While much research has shown the relationship between reciprocity and trust beliefs, the current research extends that understanding showing that in a DHP context, that effect is greater for those with higher levels of Internet experience.

Fourth, when those respondents with and without sensitive illness were compared, the results showed the path between HIPC and self-disclosure to be significant (indicating the greater influence of HIPC on self-disclosure for those with sensitive illness), as was the path between perceived reciprocity and trust (indicating the greater influence of perceived reciprocity on trust beliefs for those with sensitive illness). While the former is understandable as privacy concerns are likely to be a significant consideration inhibiting self-disclosure for those with sensitive illness (King, Brankovic and Gillard, 2012), the fact that perceived reciprocity has a greater influence on trust beliefs for those with sensitive illness is particularly valuable. Bearing in mind those with sensitive illnesses are likely to turn to DHPs in order to manage their illnesses, knowing that their trust in DHPs is most influenced by perceptions of reciprocity enables a more bounded research focus on how perceptions of reciprocity can be more effectively supported on DHPs. It again confirms the importance of the reciprocity construct in influencing trust beliefs (and through them, self-disclosure), but extends that understanding showing that in a DHP context, that effect is greater for those with sensitive illnesses.

Finally, a unique aspect of this study, and one that increases confidence in the insights obtained, relates to the research methodology that was used. The study used a triangulation process associated with mixed methods research design (Creswell and Plano Clark, 2011). Traditionally research relating to health information systems has relied heavily on quantitative research (Angst and Agarwal, 2009; Smith, Dinev and Xu, 2011; Li and Slee, 2014; Dinev *et al.*, 2016; Lowry, Dinev and Willison, 2017). While quantitative surveys offer valuable insight, in the context of an ever-evolving digital health platform environment a more comprehensive research approach is required to fully understand some phenomena. Mixed methods has long been considered more effective at understanding contemporary phenomena (Venkatesh, Brown and Sullivan, 2016) and recently researchers of information systems have highlighted the lack of mixed methods research in the area and called for more to be undertaken (O'Cathain, Murphy and Nicholl, 2010; Venkatesh and Brown, 2013). This study is among a few to contribute to a small but growing body of health information research in Ireland that utilises a mixed methods research approach. The structural design involved two stages. First a tested research instrument was used to gather quantitative survey results. Second, qualitative interviews were carried out to gain a deeper understanding of the quantitative findings. The quantitative and qualitative findings were then integrated to present a more comprehensive understanding of the nature of online self-disclosure in a personal health information context.

6.5 Towards a Meta-Framework

This section provides a description of the framework for understanding the factors that influence online self-disclosure of user health information. This framework has been developed by integrating quantitative and qualitative findings from Ireland and the U.S. and is guided by the overarching theories of SET and SPT and the supporting CPM theory. The framework is seen below in figure 6.4

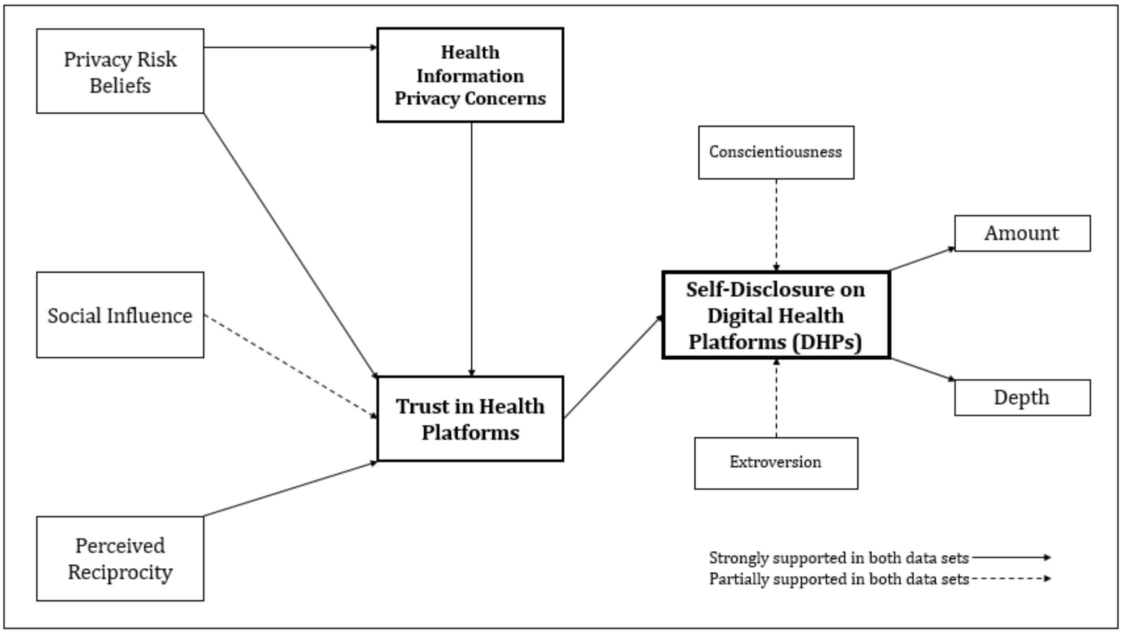


Figure 6.4 Meta-framework

The above framework represents the outcome of a comprehensive research study that has brought together contemporary variables and tested theories to produce a novel model for understanding what drives user self-disclosure of personal health information. The resulting model not only advances IS literature and its understanding of the factors that influence user self-disclosure of health information but also provides timely insights to health policy makers that wish to protect user data, and to health technology vendors that wish to develop trustworthy platforms. As greater user interaction with DHPs is expected to increase in a post covid-19 world (Rowe, Ngwenyama and Richet, 2020; Marabelli, Vaast and Li, 2021) the value of this study cannot be understated. The framework indicates that, based on the current research findings, an individual's decision to disclose health information on a digital health platform is predicted by their trust in that platform, and that this trust is shaped by a number of factors. These include general privacy risk beliefs regarding online privacy, as well as more specific concerns related to health information. These general information concerns reinforce the health information privacy concerns, and both negatively influence trust in digital health platforms. Perceived reciprocity increases trust generation and in some cultural contexts, so too does social influence. The key construct directly influencing self-disclosure of health information in this context is trust. However, two personality characteristics in particular have been shown to consistently influence self-disclosure in this context. The framework has been largely guided by SET (Thibaut and Kelley, 1959) and SPT (Altman and Taylor, 1973). SET posits that individuals initially enter into a trust based information exchange with another individual or entity if the reward is deemed greater than the cost. SPT posits that information disclosures increase when deepening, trustworthy relationships develop between individuals or entities over time. Both SET and SPT have been used in previous IS research to understand disclosures in commercial and social environments (Posey *et al.*, 2010). This study extends SET and SPT to an online health information exchange context. The constructs relating to SET and SPT will now be presented along with two constructs that relate to CPM (Petronio, 2002).

The influence of perceived reciprocity on THP was strongly supported in quantitative and qualitative data in Ireland and the U.S. This is in line with SET as information exchanges usually begin with an initial request, if the requester is perceived as trustworthy a reciprocal relationship may develop. Further to this, qualitative interviews from both countries revealed that individuals were likely to develop deeper THPs if information exchanges continued, especially if they continued to be beneficial and/or were found to be coming from close friends or family. This too is in line with SPT, as participant health information exchanges have continued over a period of time they have been shown to grown in depth and amount.

The influence of social influence on THP was supported in the quantitative and qualitative data from the U.S. and only in the qualitative data from Ireland. While this suggests a stronger role for social influence in U.S. data, its influence is partially supported in Irish data. The degree of significance attributed to social influence varied in the two countries its presence but is nonetheless evident. Participants that observed health and fitness benefits among peers in both countries indicated that this can positively influence one's likelihood to trust a DHP. As a result, this construct is in line with SET and SPT due to participants increased disclosures in a platform they deem trustworthy and reciprocal.

The influence of privacy risk beliefs on THP and HIPC was strongly supported in quantitative and qualitative data from Ireland and the U.S. That is to say that if an individual perceived a privacy risk they were likely to reduce their THP. Conversely if an individual perceived a risk to their privacy their HIPC was likely to increase. This finding is further evidence for the presence of SET and SPT. Both of these theories claim that while individuals may share personal information they can also cease to share information or at least reduce information sharing if a risk greater than the reward is perceived. Further to this, it supports the observation of CPM (Petronio, 2002), which claims that individuals actively monitor risks that might impact the management and ownership of their personal information. In doing so

CPM posits that as more people or entities become aware of private information the more this information is at risk and therefore privacy management is required. The qualitative interviews found that individuals can take data management actions into their consideration when a risk is perceived.

The influence of HIPC on THP was strongly supported in quantitative and qualitative data from Ireland and the U.S. If an individual exhibited HIPCs it was found that this would likely reduce their THP. Again this is in line with SET and CPM which both claim individuals will reduce or cease sharing of personal information if a risk is perceived. Qualitative interviews did reveal that HIPC could be reduced however if an individual's health information was to be used for public health and if this was made known to them, thus assisting in their management and ownership knowledge. Such personal management of data would be in accordance with CPM.

The influence of THP on self-disclosure was strongly supported in quantitative and qualitative data from Ireland and the U.S. When THP was present self-disclosure was shown to increase. Qualitative interviews added that trustworthy design, regular updates and information quality played a significant factor in long term THP and disclosures. This revelation echoes research that utilises SET and SPT to understand the relationship between trust and self-disclosure in non-health information platforms (Posey and Ellis, 2007; Posey *et al.*, 2010). This finding is in line with SPT, which claims that as an environment is deemed trustworthy more disclosure is likely to occur.

Two personality traits were found to be present and influential in both Irish and U.S. data. Conscientiousness was found to decrease self-disclosure while extroversion was shown to increase self-disclosure. These finding are partially supported in both countries as they are present in the quantitative and qualitative data from the U.S. and emerge in Irish data via the qualitative findings. Conscientiousness is associated with reduced self-disclosure as individuals displaying this trait can be risk aversive, a feature of SET and SPT. Conversely extroversion is associated with increased self-disclosure as individuals displaying this trait can be more open to social exchanges, again this is a feature of SET and SPT.

Finally, self-disclosure was shown to occur across two dimensions: amount and depth. Amount refers to whether a communicated disclosure of personal experience or information occurs frequently or infrequently and also to the duration of time over which it occurs. Contemporary research has shown that the advancement of a relationship is dependent on the amount of communication (Bansal, Zahedi and Gefen, 2010; Joinson *et al.*, 2010; Al-Saggaf and Nielsen, 2014). Depth refers to whether or not a communication reaches a satisfactory degree of intimate revelation. Previous research reveals depth and intimacy to be integral to developing relationship closeness and penetration of a network (Altman and Taylor, 1973). These findings again are in line with SET and SPT. According to SET an initial trusting information exchange is said to be predicated on frequent disclosures while SPT claims that deeper revelations occur over time as a reciprocal relationship develops.

This framework represents an extension of SET and SPT to an online health information exchange context. In doing so it answers calls for further examination of self-disclosure in different CMC contexts and for the exploration of prominent communication theories in new online contexts (Nguyen, Bin and Campbell, 2012). Further to this the study makes a significant contribution to IS research with particular focus on THP and HIPC and the influence they have on user self-disclosure of health information. The framework indicates that perceived reciprocity and social influence can have a positive influence on THP, while privacy risk beliefs can negatively influence THP and positively influence HIPC. HIPC is shown to reduce THP, resulting in HIPC having an indirect effect on self-disclosure via THP. THP is revealed to have a significant positive influence on self-disclosure. Conscientiousness has been shown to have a negative influence on self-disclosure while extroversion can have a positive influence on self-disclosure. Finally, self-disclosure itself was shown to occur across two dimensions: amount and depth. In summary, this framework offers a unique multicultural insight into the factors that drive user self-disclosure of health information on DHPs.

6.6 Implications for Practice

This study has generated a number of valuable insights for practice. These insights can be utilised by health technology vendors, e-governance and policy makers, and online behavioural psychologists. The following section will outline the implications and recommendations for practice across these three categories.

1. Health Technology Vendors:

User disclosure of health information on DHPs is a critical success factor for health technology vendors. This study has revealed that the critical pathway to user self-disclosure is via THP. Despite this, individuals express a number of privacy and trust related concerns pertaining to health technology vendors, each of which impede disclosure behaviour.

First, individuals lack awareness as to how health technology vendors use and access their data, which can increase HIPC. When individuals experience increased HIPC this can in turn reduce THP and as a result disclosure behaviour can be reduced. Individuals are more likely to experience increased HIPC if DHPs present complex or opaque information when a user tries to ascertain how their personal data is being used. To overcome these issues, technology vendors could develop solutions to inform and alert users as to how their data is being used in real time via a privacy dashboard, thus reducing HIPCs. Another option would be to allow for adaptive sharing of personal data (Yu, Bandara and Nuseibeh, 2014), as this would increase user agency and awareness of who has access to their data. Furthermore, vendors could incorporate 'privacy-by-design' principles at the design stage of DHPs (Perera *et al.*, 2016). This would imply DHPs have for example minimised data retention periods, minimised data acquisition policies, data anonymization, encrypted storage and reduced data granularity, and that these features are clearly communicated to users. If vendors were transparent and communicated these design principles to users this could reduce HIPCs and increase THP.

Second, individuals with digital skills competence express lower HIPCs and greater willingness to disclose health information on DHPs. As such, efforts from health technology vendors to create informative and educational DHPs may reduce privacy concerns and indirectly increase disclosures amongst groups with lower digital skills competence and experience. Users could for example be warned if their disclosure behaviour is putting them at risk, as noted by Hallam and Zanella, (2017). This would be in line with Dinev *et al.*, (2016) and Hwang *et al.*, (2012), who have previously indicated that users should be educated as to the benefits and technical aspects of digital platforms.

Third, individuals' HIPCs can be reduced if it is made clear to them that their health information is being used for the benefit of public health. Recent research elaborates on this issue and indicates that consent models for public health can positively increase disclosure levels while reducing concerns (Köngeter *et al.*, 2022). If DHPs are transparent in these endeavours individuals are more likely to express reduced HIPCs and increased THPs. User disclosures are critical to DHPs and the reduction of user concerns and increased awareness of benefits have been shown to increase user disclosures (Ozdemir, Smith and Benamati, 2017), as such transparent use of user data for the benefit of public health may decrease HIPCs and indirectly increase disclosure behaviours.

Fourth, trustworthy platform design is critical for user engagement and the realisation of positive health outcomes from DHPs. Individuals have expressed low trust levels in DHPs that are non-intuitive, lacking in quality information, poorly updated and low in community engagement. It is apparent that users associate poor platform design with low competence and low integrity. It is recommended that improved functionality, reliability and helpfulness can remedy these issues (Lankton, Mcknight and Tripp, 2015). This could be realised via regular updates, real time information provided by accredited physicians or health and wellness entities and adaptive design principles.

Finally, individuals have indicated that developing reciprocal connections on DHPs can increase their THP. As vendors rely more on disclosures, functional and interactive community development should be considered paramount to developing THPs and reducing HIPCs (Ozdemir, Smith and Benamati, 2017).

2. E-governance and Policy Makers:

In a post covid-19 world, governments and public health bodies are increasing the usage of digital first health solutions (Rowe, Ngwenyama and Richet, 2020; Alfayez *et al.*, 2021; Marabelli, Vaast and Li, 2021; Ghose *et al.*, 2022). DHPs represent an important mechanism to facilitate such strategic policies. This means, however, that it is imperative to realise the potential benefits and challenges to deploying DHPs while generating user disclosure on these DHPs in the most secure manner. While this study collected data prior to the pandemic, it nonetheless produces findings that only enhance key lessons from many post covid-19 research studies. The first lesson relates to e-governance and crisis management. Rowe, Ngwenyama and Richet, (2020) have highlighted that without proper trustworthy design of DHPs, certain target groups in a population can experience reduced usage of DHPs, which in turn results in alienation of these groups. If some population groups are omitted from DHPs, the result can be detrimental to the general population, due to an incomplete dataset of citizen experience during a crisis. This is of particular concern as incomplete public health datasets could lead to skewed data, discrimination and increased inequality (Marabelli, Vaast and Li, 2021). Vieira Silva *et al.*, (2022) have also shown that a crisis such as covid-19 reduces health care access to some groups such as the elderly. With all this taken into consideration, it is recommended that e-governance and public policy entities engage with health technology vendors and have an active role in the design process of DHPs intended for public health, as this study has already shown that THP is partially generated by a trustworthy platform design and that THP has a significant influence on user self-disclosure.

Next, individuals have expressed higher levels of self-disclosure on DHPs when they feel competent and informed on how to use them and how their data is used by them; it is therefore recommended that public health entities should engage in educational programs to upskill target groups that are in danger of not adopting new DHPs. However, overexposure to DHPs, especially post-crisis can lead to a sense of institutionalised control and digital scarring (Marabelli, Vaast and Li, 2021). Based on the findings from this study it is advised that DHPs and their accompanying policies abide by non-invasive notification systems and best in practice data protection standards.

Another key lesson for e-governance and policy makers relates to mHealth and Telehealth. mHealth and Telehealth solutions represent a powerful tool in the effort to reduce the economic burden that rests on stressed health care systems, caregivers and patients (Frontera *et al.*, 2016; Alfayez *et al.*, 2021), and this is especially apparent in a post covid-19 world. However, research shows that in order for mHealth and Telehealth solutions to flourish, it is critical that users experience positive engagement with DHPs (Ghose *et al.*, 2022). This present study, in unison with previous research, has revealed that individuals expressed greater levels of health and wellbeing when using DHPs. This is line with Ghose *et al.*, (2022) who have shown that individuals who experience postive outcomes from DHPs are more likely to reduce physical visits to hospitals and increase their usage of Telehealth solutions instead. This in turn can lead to a reduction on the workload and economic burden that rests on stressed health care systems. It is therefore recommended that e-governance and policy making entities undertake quantitative and qualitative reviews of the user experience of DHPs in order to implement continuous improvements that enhance users' health outcomes.

Finally, more and more government and public health bodies are sharing data from mHealth solutions with private health companies (Braunack-Mayer *et al.*, 2021); however this same research notes that it is imperative to understand user attitudes to this in order reduce HIPCs. This finding corresponds with participant's experience in this current study. As noted in the previous section, when individuals are informed of their health information being shared for the benefit of public health they are more willing to participate in health information disclosure. It is, however, noted that not all individuals are willing to have their personal health information shared for secondary or public health use. Furthermore, individuals express a lack of awareness as to how their information is accessed which in turn can increase their HIPC. Building on previous recommendations it is advised that e-governance and public policy entities engage with health technology vendors to develop transparent consent mechanisms. Köngeter *et al.*, (2022) have proposed solutions that are recommended for the present study. A number of consent models could be offered to users such as 1) broad consent, 2) specific consent, 3) renewed consent based on time intervals, and 4) no consent. Adoption of these mechanisms might assist in the reduction of HIPCs and an increase in THPs. In addition, it is recommended that the transfer of user health data only occurs across countries of comparable data protection standards(Köngeter *et al.*, 2022).

3. Online Behavioural Psychologists:

Online behavioural psychologists have a history of active and productive collaboration with health and I.S. researchers. Indeed, these collaborations often result in the development of important health intervention strategies that promote health and wellbeing (Rothman, Klein and Cameron, 2013). Recent research has not only highlighted the need to extend this collaborative tradition, but to increase such multidisciplinary research with a focus on personality traits and their influence on online health interventions (Rothman, Klein and Cameron, 2013; Strickhouser and Zell, 2017; Bogg and Milad, 2020). Researchers have, for example, shown that individuals with high trait anxiety can experience increased levels of worry when exposed to health concerns via media and digital platforms (Schmidt *et al.*, 2022). Other works reveal that individuals high in trait conscientiousness adhere more to digital health interventions than those high in neuroticism and extroversion (Bogg and Milad, 2020). Indeed Strickhouser and Zell, (2017) have shown certain personality traits to be predictors of overall health and wellbeing. This present study improves on our understanding of online behaviour with regard to connected health platforms and personality traits. In doing so it offers a timely insight as to how personality traits influence self-disclosure of health information online. For example, Irish individuals high in trait neuroticism were shown to increase self-disclosure while extroversion and conscientiousness was shown to influence self-disclosure in both Ireland and the U.S. Online behavioural psychologist could use these insights to recommend tailored DHPs for individuals displaying different personality trait tendencies. It may, for example, be more effective for people high in trait conscientiousness to experience health notifications with greater detail and information than those of another disposition. It is therefore argued that online behavioural psychologists can develop informed psychological interventions during DHP development that are enhanced by personality trait insights garnered from I.S. research (Herbert, El Bolock and Abdennadher, 2021). To this end Bogg and Milad, (2020) recommend that DHPs should clearly communicate the benefits and costs of user interaction with DHPs. Furthermore, it is recommended that online behavioural psychologists consider engaging with both e-governance entities and health technology vendors at the early design stage of DHPs.

In summary, this study provides actionable insights that can be adhered to by health technology vendors, e-government and policy makers, and online behavioural psychologists. The study highlights the drivers of THP and HIPC, it then reveals that

HIPC can inhibit THP, which in turn influences self-disclosure. Furthermore, personality traits are shown to influence self-disclosure behaviours. Recommendations have been made to leverage these insights.

6.7 Conclusion and Summary of Contributions

This research set out to examine the factors that influence user self-disclosure of personal health information on digital health platforms. In doing so it has illustrated the route to self-disclosure of health information in an online context. Significantly, it presents contributions that are in contrast to previous findings within the IS community (Bansal, Zahedi and Gefen, 2010; Fox and Connolly, 2018). As a result, this research reveals that HIPC does not directly influence self-disclosure of health information but that it does influence self-disclosure indirectly via THP. Furthermore, HIPC is revealed to negatively influence THP. THP is shown to be generated by three key factors; perceived reciprocity, privacy risk beliefs and to a lesser extent social influence, while HIPC is accentuated by privacy risk beliefs. Additionally, THP is confirmed as the critical pathway to self-disclosure of health information in an online health context. Finally, the personality trait of conscientiousness was shown to reduce disclosure behaviour in an online health context while extroversion and to a lesser extent neuroticism were shown to increase disclosure behaviour in an online health context. A framework guided by SET, SPT and CPM has then been produced and tested with quantitative surveys and qualitative interviews. The cumulative findings offer empirical and theoretical contributions to I.S. literature and provide actionable insight to health technology vendors, e-government and policy makers, and online behavioural psychologists. The following chapter will address limitations of the study and directions for future research.

7 Chapter Seven: Conclusion

7.1 Introduction

This study set out to explore the factors that influence user self-disclosure of personal health information on digital health platforms. It proposed that online self-disclosure is influenced primarily by trust in health platforms (THP) and indirectly by health information privacy concerns (HIPC) across different cultures, personality traits, and perceptions. The study followed a sequential mixed-methods research approach. First, a quantitative survey was used to collect data from participants in Ireland and America. Second, follow-up qualitative research interviews were conducted with Irish and American participants to develop deeper understandings of the proposed relationships. The quantitative and qualitative findings were then integrated and evaluated in the context of the hypothesised relationships.

The structure of the dissertation was as follows: Chapter One presented the need and justification for the study and provided an overview of the research objectives and key hypotheses. Chapter Two presented the underlying literature that has guided the study along with theoretical considerations and research hypotheses. Chapter Three presented the research methodology for the study and an explanation of the research framework employed for the study. Chapter Four presented the results of the quantitative testing of the research framework. Chapter Five presented the findings of the qualitative interviews. In this chapter the quantitative and qualitative were integrated and meta-inferences were developed. Chapter Six presented the research contributions of the study, a revised framework and implications for practice. This final chapter draws conclusions on the contributions of this study along with limitations of the study and future directions for research.

7.2 Contributions to Theory

This section provides an overview of the contributions of this study by revisiting the gaps in literature identified in Chapter Two and illustrating how this study fills these gaps and adds to our understanding of online self-disclosure in a health context.

(i) Gap in understanding the antecedents of self-disclosure in an online health context

Many previous studies have explored online self-disclosure in a commercial and social contexts (Joinson, 2001; Posey and Ellis, 2007; Joinson *et al.*, 2010; Posey *et al.*, 2010; Jiang, Bazarova and Hancock, 2013). There is however a limited number of studies to address it in a health context (Bansal, Zahedi and Gefen, 2010). This current study has extended self-disclosure antecedents from commercial research, confirmed their existence in an online health context and repositioned their directional relationship with self-disclosure. As a result, this study has identified THP as the critical generator of self-disclosure and has revealed that HIPC influences self-disclosure indirectly, through its effect on THP. It further shows that the effect of HIPC is accentuated by more general privacy risk beliefs, which along with social influence, perceived reciprocity and privacy risk beliefs, influence the formation of THP. Additionally, personality traits were shown to influence online self-disclosures of health information, particularly extroversion and conscientiousness. By elucidating these relationships and their effects, this study provides comprehensive insight into the factors, dynamics and relationships which lead to self-disclosure in a digital health platform context. This is a timely and crucial contribution in a post Covid-19 world where user exposure to digital health platforms has seen a marked increase.

(ii) The Role of Trust in Online Disclosure of Health Information

The study of trust in online contexts is not new. However contemporary IS research has identified a gap in our understanding as to how trust differs from previous understandings when studied in an online health context and on DHPs (Vega, Montague and DeHart, 2010; Adjekum, Blasimme and Vayena, 2018; Kim, 2018). This study has confirmed that THP has constituent layers, namely platform design, information quality, reputation and trust in health technology vendors. Moreover, this study has shown that THP is positively influenced by perceived reciprocity and social influence and negatively influenced by privacy risk beliefs and HIPCs. Significantly, this study has revealed that the critical pathway to self-disclosure of health information is through the generation of THPs.

(iii) The role of HIPC in generating THP and self-disclosure

Previous research has measured information privacy concerns in an electronic health record (Fox and Connolly, 2018). There is however a gap in knowledge with regard to how HIPCs influence THPs and self-disclosure. This study has developed our understanding of the relationship between THP and subsequently self-disclosure. The findings reveal the direction of the relationship between HIPC and THP. It is shown that HIPC can reduce THP which in turn can reduce disclosure behaviours. Further to this, the study reveals HIPC to have an indirect relationship with online self-disclosure of health information, this finding is in contrast to previous research which found a direct relationship between HIPC and intention to disclose (Bansal, Zahedi and Gefen, 2010) Moreover, general privacy risk beliefs have been shown to accentuate HIPC, further adding to the research contribution of this study. This study has extended the HIPC measure to online trust and self-disclosure, used across two countries it provides a timely and critical contribution to HIPC literature.

(iv) Extending theories to a new context

Online health information studies have used a number of underlying theoretical frameworks to investigate different phenomena, utility theory, protection motivation theory and social cognitive theory being examples (Bansal, Zahedi and Gefen, 2010; Fox and Connolly, 2018). However, self-disclosure is an action involving the exchange of personal information for a perceived benefit. That disclosure is characterised by considerable vulnerability, a vulnerability that is heightened in an online health context. The greater the level of trust (and strength of factors influencing that trust generation) associated with disclosure experiences, the more likely it is that the depth and extent of those disclosures will continue. Previous studies of health technology adoption in an online context have tended to focus on information privacy risks or social influence, choosing theoretical frameworks which align with that focus, but as their focus has tended to be adoption of a particular technology, they did not consider either disclosure or extent of that disclosure and how it relates to the trust forming antecedents. For that reason, the present study has extended SET and SPT to an online health context. These theories have been used previously in online disclosure studies albeit in commercial contexts (Posey and Ellis, 2007; Posey *et al.*, 2010). The current study therefore represents an extension of SET and SPT to an digital health context, demonstrating its value within such a context, and responding to calls for the leveraging of existing theories to new contexts (Nguyen, Bin and Campbell, 2012).

(v) Mixed Methods research

This study employs a mixed methods research approach. This methodology has been underused for some time and researchers have called for more use of it in IS research (Venkatesh, Brown and Bala, 2013; Venkatesh, Brown and Sullivan, 2016). As the study of digital health platforms and user disclosures is a critical and growing research area a mixed methods research approach can provide comprehensive insight to the phenomenon. The structural design of this study involved two stages. First a tested research instrument was used to gather quantitative survey results. Over 300 surveys from Ireland and the U.S. were tested. Second, 20 qualitative interviews with Irish and U.S. citizens were carried out to gain a deeper understanding of the quantitative findings. The initial quantitative analysis provided valuable, robust insights about the strength and direction of relationships between key constructs in this study (e.g. HIPC and THP). Equally important the follow-up qualitative interviews allowed for the human experience to come through the data. The qualitative interviews for example allowed individual privacy concerns to come to light while also revealing some variables to have influential roles when their significance was not apparent in the quantitative analysis (e.g. social influence and conscientiousness in Irish data), these key insights would have been lost without a mixed methods research approach. The quantitative and qualitative findings were then integrated to present meta-inferences. The output of this was a comprehensively tested framework that adds to our understanding of the nature of online self-disclosure in a personal health information context.

7.3 Overview of the Framework

This study has produced a number of contributions to the body of knowledge that have been outlined in detail in the previous chapter. The culmination of these contributions is a comprehensive framework for examining the factors that drive user self-disclosure of personal health data on digital health platforms. This section provides a brief overview of the framework so as to illustrate how this study can provide a foundation for future research on user self-disclosure of health information in a post covid-19 world.

The framework that this study produces proposes that user self-disclosure of health information is a complex phenomenon shaped by individual characteristics, perceptions and culture. In line with SET (Thibaut and Kelley, 1959), this study shows that individuals go through a cognitive process of weighing up perceived benefits and risks before disclosing information. Furthermore, the study is supported by SPT (Altman and Taylor, 1973), as individuals experience reciprocation and trust over time, they are willing to disclose in greater amount and depth. The framework is also supported by CPM theory (Petronio, 1991), which posits that individuals also attempt to manage their personal information by creating privacy boundaries. With these guiding theories, the framework proposes that individuals are initially influenced by privacy risk beliefs, social influence and perceived reciprocity. These three factors then have knock-on effects on one’s trust in health platforms. Both social influence and perceived reciprocity can positively influence THP while privacy risk beliefs can reduce one’s THP. Health information privacy concerns are accentuated by privacy risk beliefs and are not influenced by social influence and perceived reciprocity. THP is then shown to be negatively influenced by HIPC. THP then has a direct positive relationship with self-disclosure of health information. Finally, the personality traits of extroversion, conscientiousness and to a lesser extent neuroticism are shown as having an impact on one's likelihood to self-disclose health information on DHPs.

7.4 Limitations and Future Research

While this study makes a number of valuable contributions to research and practice, there are a number of limitations to this study. Firstly, this study represents examination of health disclosures on digital health platforms but does not focus on any one ailment or on any one digital health platform, instead this study represents an insight into health disclosures across an array of digital health platforms, where the focus is on the critical pathway of influence to self-disclosure. While this is beneficial in developing general assumptions about the phenomenon of self-disclosure on DHPs it also opens possibilities for future research that is more focused. To further advance our understanding of self-disclosure in a digital health context future studies could focus on disclosures by participants suffering with a specific aliment or disclosures by participants using a specific digital health platform. Future research could potentially shed light on altered disclosure behaviours when specific illnesses are examined, while examination of specific digital health platforms could elucidate if trust in health platforms changes according to specific design principles.

Second, this study's sample is made up of a broad representation of society in both Ireland and the U.S. The sample contains a mixture of different age groups and demographics from both countries. While effort was made to capture insights from a diverse section of society there are some innate limitations. The result is a lack of focus on any one age bracket within society. This limitation represents another opportunity for future research. Whilst the sample allows for generalisation, a more focused sample could provide more nuanced insights about a particular societal group or age bracket such as retirees. Further to this, the post-hoc tests present a number of opportunities for future research pertaining to socio-demographics. With regard to occupation two groups were examined, those who were employed (including self-employed) and those who were students or not employed. Compositional invariance was obtained for all constructs other than conscientiousness, social influence, and trust. The MGA test showed that the path from social influence to HIPC was significant as was the path from trust to self-disclosure. However, as compositional invariance was not obtained for social influence or trust, we cannot be sure that this represents a real difference between the groups, or if it results from interpretational differences. Previous research in a health context has provided conflicting results. In a Taiwanese study on privacy concerns about EHRs occupation was not found to have an influential role in participants privacy concerns (Hwang *et al.*, 2012), while an Australian study about privacy concerns and health databases revealed unemployed participants to have reduced HIPC (King, Brankovic and Gillard, 2012). These mixed results indicate that future research attention should examine the influence of occupation on variables such as HIPC, THP and social influence, moreover the role culture and occupation should be highlighted.

Third, this study was limited to participants who could speak English and did not include participants without prior experience with DHPs. Non English speakers may provide deeper cultural insights while participants without prior experience may hold different trust and privacy views.

The fourth and final limitation of this study relates to timing. This study collected data about participant views towards self-disclosure, trust, privacy and digital health platforms before the Covid-19 pandemic, thus limiting participant insights to pre Covid-19 experiences. While the insights garnered from this study provide valuable research contributions and implications for practice, and while these insights have proven to be in line with many post Covid-19 studies (Bogg and Milad, 2020; Rowe, Ngwenyama and Richet, 2020; Alfayez *et al.*, 2021; Herbert, El Bolock and Abdennadher, 2021; Marabelli, Vaast and Li, 2021; Stuart *et al.*, 2022; Vieira Silva *et al.*, 2022), there is a future research opportunity to assess this study's framework with participants post Covid-19. Indeed, global citizens are now more experienced and competent with DHPs and their attitudes and behaviours towards self-disclosure, trust, privacy and digital health platforms are likely to have evolved since the data for this research study was collected. Future studies could reveal enhanced roles for trust and design principles, for example.

7.5 Summary

Despite the limitations of this study, it does make a number of valuable contributions to research and practice relating to online trust in health platforms, privacy concerns, self-disclosure and IS literature. These contributions include the empirical support for the extension of several constructs and theories to an online health information exchange context. These extensions are enhanced by a comprehensive mixed methods research approach with data from two countries. The final framework shows that self-disclosure is shaped by number of factors, characteristics and perceptions and that the critical pathway to self-disclosure of citizen health information on digital health platforms is via trust in health platforms. The framework provides a strong bedrock for future studies in a post Covid-19 world, while the contributions from the study provide timely and critical insights for health technology vendors, e-government policy makers and online behavioural psychologists. Table 7.1 below provides an overview of this studies contributions.

Area of Contribution	***This Study***	***Future Research***
Empirical	This study revealed that: Self-disclosure in a digital health platform context is directly influenced by trust in that platform. HIPC has an indirect negative relationship with self-disclosure via THP. General privacy risk beliefs negatively influence both HIPC and trust Perceived reciprocity and to a lesser extent, social influence, influence THP.	This research has responded to calls for research that: explores the antecedents of trust in heath platforms (Kim, 2016), explores HIPC (Fox and James, 2020), explores dimensions and drivers of online self-disclosure (Shih, Lai and Cheng, 2017) and examines the role of personality traits and culture in health disclosures (Bansal, Zahedi and Gefen, 2010). Building on the current research, *further empirical work* can be undertaken to examine the antecedents of self-disclosure in relation to specific health data categories, including chronic conditions such as diabetes and more sensitive health conditions which has higher associated disclosure costs.
Theoretical	Social influence may not be culture independent. Extroversion, conscientiousness and neuroticism can influence one's disclosure behaviours and may not be culture independent. This study extends SET and SPT to an online health information context	This research has responded to calls for studies that extend previous CMC theories to new contexts (Nguyen, Bin and Campbell, 2012). Building on the current research, *further theoretical insights* may be gained by applying both CMC and SPT to research examining disclosure behaviours in other are more sensitive online contexts, including online psychological support services.

		The confirmed role of reciprocity in this study is important. It is closely associated with online engagement – and as engagement has been shown to be a predictor of trusting response outcomes - this indicates that a more granular examination of the relationship between reciprocity *and engagement* in terms of reciprocity motivates engagement and how both shape self-disclosure in an online health context merits further attention.
Method	This study utilised a mixed methods research approach. Quantitative surveys were used followed by probing qualitative interviews. Meta-inferences were then developed from the findings.	This research responded to the call for research which extends the use of a mixed methods research approach in I.S. studies (Venkatesh, Brown and Bala, 2013). Although the quantitative research yielded important insights, those insights are bounded by survey structure limitations, and it was the combination of both qualitative with quantitative data capture and analysis which provided the richness of insight obtained in this study. For that reason, other researchers may wish to use the current research as a foundation for *new combinatorial methods* of examining self-disclosure, which will enable them to gain richer information from their data. This could include inductive research that delves more deeply into the role of specific antecedents such as social influence, through sentiment analysis which focuses on the valence of health information disclosure on online forums, or through use of Q Method which provides a deeper focus on the individual and their characteristics. Similarly, the use of newer approaches such as fuzzy set qualitative comparative analysis (FsQCA) which enable identification of specific cases in a sample and their characteristics to delve into the degree to which those cases verify the specific propositions, would contribute to our understanding of self-disclosure outcomes

Context	This study collected data from Ireland and America and had a focus on the role of trust specific to health.	This study responded to the calls for cross cultural studies that examine I.S. platforms with regard to privacy and (Bélanger and Crossler, 2011; Lowry, Dinev and Willison, 2017) as well as calls for research exploring how the trust construct is specific to the domain of health (Vega, Montague and DeHart, 2010). However, rather than employing samples with obviously contrasting cultural dimensions, the samples used in this study are drawn from English-speaking first world countries with many commonalities. However different results were obtained for both in relation to a number of important relationships including social influence, extroversion and neuroticism. This confirms the need for further research work which moves beyond use of samples with explicitly different cultural dimensions, and also the need to move beyond the assumption that first world countries or English speaking countries will provide similar results. The results of this study confirm otherwise. Therefore, further studies examining self-disclosure of health information in online contexts, utilizing samples drawn from nationally similar contexts or regions represents an important avenue of research that may provide insights into cultural or regional variation in antecedents or disclosure amount and depth. Additionally, future research samples could focus on specific age brackets such as retirees, specific DHPs such as blood pressure monitor applications and specific illnesses such as diabetes.
Practice	The findings provide actionable insights for health technology vendors and public health entities which can increase citizen self-disclosure of health information in a secure manner.	This study responded to calls for trust, privacy and personality to be explored in order to foster safe disclosures on DHPs (Bansal, Zahedi and Gefen, 2010; Rothman, Klein and Cameron, 2013; Lowry, Dinev and Willison, 2017).

Table 7.1 Summary of Contributions

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APPENDIX A: ETHICAL APPROVAL

The image part with relationship ID rId22 was not found in the file.

APPENDIX B: SURVEY INVITATION EXAMPLE

The image part with relationship ID rId22 was not found in the file.

APPENDIX C: SURVEY INSTRUMENT

Welcome!

This study is interested in understanding why people reveal personal health information to online health platforms. This study is being conducted by Eoghan Mc Conalogue from Dublin City University, Ireland, under the direction of Dr. Adela Grando from Arizona State University. This research is supported by the ASU-DCU Transatlantic Partnership and the Higher Education Authority Mobility fund.

Participation in this research involves completing this questionnaire and will take approximately 15 minutes of your time. Please read the instructions for each section carefully and answer the questions to the best of your ability. The information you provide will be anonymous.

If you are interested in the findings of the study or have questions, you can email the researcher eoghan.mcconalogue@dcu.ie . For more information on the ASU-DCU Transatlantic Partnership, please visit: https://dcu.asu.edu/ By clicking the button below, you acknowledge that your participation in the study is voluntary, you are an English speaker of 18 years or older, (student, employed, retired) who has interacted at least once with an online health platform (Ex. Fitbit, WebMD, Apple Health, HealthVault, heart rate monitor, personal health record systems, online health communities) and that you are aware that you may choose to terminate your participation in the study at any time.

If you have any questions about your rights as a subject/participant in this research, or if you feel you have been placed at risk, you can contact the Chair of the Human Subjects Institutional Review Board, through the ASU Office of Research Integrity and Assurance, at (480) 965-6788.

Do you consent?

- ○ Yes

Approximately how long have you been using the Internet?

- ○ Less than 1 year
- ○ 1 - 5 years
- ○ 5-10 years
- ○ 10-15 years
- ○ >15 years

Which of the following technologies do you use to access the internet? (Please tick all that apply)

☐ Personal Computer (PC)

☐ Laptop

☐ Smartphone/ mobile phone

☐ Tablet

☐ Other, please specify: ____

Please select the option that indicates how often you engage in each of the following internet activities.

	Never	Once a month or less	2-3 times a month	1-3 times a week	4 times a week / every day
I use the Internet for personal purposes (e.g. email, social networking)	○	○	○	○	○
I use the Internet for work or study purposes	○	○	○	○	○
I search online for information related to disease diagnosis and treatment	○	○	○	○	○

I search online for information related to health management (exercise, diet, mental health, etc.)	○	○	○	○	○
I search online for health information for education, research or learning purposes	○	○	○	○	○

I purchase health products such as health food and medical equipment online	○	○	○	○	○
I use social media (e.g. Facebook, Twitter) as a source of health information	○	○	○	○	○
Exercise or fitness applications	○	○	○	○	○
Diet, food, or calorie tracking applications	○	○	○	○	○

Blood pressure monitoring applications	○	○	○	○	○
Applications related to pregnancy	○	○	○	○	○
Diabetes applications	○	○	○	○	○
Medication management applications	○	○	○	○	○
Sleep tracking applications	○	○	○	○	○
Mood monitoring applications	○	○	○	○	○

Health information applications (e.g. WebMD)	○	○	○	○	○

Please select the option that indicates how often you use each of the following health technologies

	Never	Once a month or less	2-3 time a month	1-3 times a week	4 times a week / every day
Health Monitoring Devices (e.g. FitBit, Jawbone, Heart rate monitor)	○	○	○	○	○
Personal Health Record systems (e.g. Microsoft Healthvault)	○	○	○	○	○

End of Block: Technology Experience

Start of Block: Online self-disclosure

This section includes questions about your self-disclosure of personal health information using online health platforms.

Personal health information can include information about pregnancy, medication, mental health, fitness, diet, sleep, chronic illness.

Online health platforms include any website or smartphone application that allows you to seek and store personal health information about pregnancy, medication management, mental health, fitness, diet, sleep or chronic illness, (WebMD, FitBit or Apple Health for example).

Please identify how much you disagree or agree with each statement.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I often discuss my feelings about my health online	○	○	○	○	○	○	○
I usually discuss my health for fairly long periods at a time online	○	○	○	○	○	○	○

I spend little or no time discussing my own health online	○	○	○	○	○	○	○
I often discuss my health online	○	○	○	○	○	○	○

	strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I intimately disclose who I really am, openly and fully in my interactions about my health online	○	○	○	○	○	○	○

I often disclose intimate, personal things about my health without hesitation online	○	○	○	○	○	○	○
I feel that I sometimes do not control my self-disclosure of personal health information online	○	○	○	○	○	○	○

Once I get started, I intimately and fully reveal personal health information in my self-disclosures online	○	○	○	○	○	○	○

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I always feel completely sincere when I reveal my own feelings and experiences about my health online	○	○	○	○	○	○	○

My online self-disclosures about my health are completely accurate reflections of how my health really is	○	○	○	○	○	○	○

My statements online about my own feelings, emotions, and experiences relating to my health are always accurate self-perceptions	○	○	○	○	○	○	○

I am always honest in my self-disclosures relating to my health online	○	○	○	○	○	○	○

Online self-disclosure of personal health information

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
When I express my personal feelings relating to my health online, I am always aware of what I am doing and saying	○	○	○	○	○	○	○

When I reveal my feelings about my health online, I consciously intend to do so	○	○	○	○	○	○	○
When I am self-disclosing my health information online, I am consciously aware of what I am revealing	○	○	○	○	○	○	○

	strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I usually disclose positive things about my health online	○	○	○	○	○	○	○
I normally express my “good” feelings about my health online	○	○	○	○	○	○	○

Overall, my disclosures about my health online are more positive than negative	○	○	○	○	○	○	○

End of Block: Online self-disclosure

Start of Block: Trust in platform

Based on your experience with technology vendors (e.g. websites, smartphone applications) for all purposes (including but not limited to health), please identify how much you disagree or agree with each statement.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I think technology vendors are always honest when it comes to using my health information	○	○	○	○	○	○	○
I think technology vendors care about customers	○	○	○	○	○	○	○

I think technology vendors are opportunistic when using my health information	○	○	○	○	○	○	○
I think technology vendors are predictable and consistent with regards to using my health information	○	○	○	○	○	○	○

I think technology vendors are competent and effective in providing their services	○	○	○	○	○	○	○
I trust that technology vendors keep my best interests in mind when dealing with my health information	○	○	○	○	○	○	○

It would be risky to disclose my personal health information to technology vendors	○	○	○	○	○	○	○
There would be high potential for loss associated with disclosing my personal health information to technology vendors	○	○	○	○	○	○	○

There would be too much uncertainty associated with giving my personal health information to technology vendors	○	○	○	○	○	○	○

Providing technology vendors with my personal health information would involve many unexpected problems	○	○	○	○	○	○	○

Based on your experience with technology vendors (e.g. websites, smartphone applications) for all purposes (including but not limited to health), please identify how much you disagree or agree with each statement.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I trust online health platforms with an intuitive layout	○	○	○	○	○	○	○
I trust online health platforms that are clear and easy to navigate	○	○	○	○	○	○	○

An online health platform with an intuitive layout would make it easier for me to share information	○	○	○	○	○	○	○
I trust health technology vendors that place advertisements on an online health platform	○	○	○	○	○	○	○

I trust health technology vendors with a .org domain	○	○	○	○	○	○	○
I trust health technology vendors with a .com domain	○	○	○	○	○	○	○
I trust health technology vendors with a .edu domain	○	○	○	○	○	○	○
I trust health technology vendors with a .gov domain	○	○	○	○	○	○	○

I trust health technology vendors with a .io domain	○	○	○	○	○	○	○
I trust online health platforms that provide regular information updates	○	○	○	○	○	○	○
I trust online health platforms that provide clear and consistent messaging	○	○	○	○	○	○	○

I trust online health platforms that provide professional certification (ex. medical board certification)	○	○	○	○	○	○	○

End of Block: Trust in platform

Start of Block: Social influence to use an online health platform

This section includes questions related to social influence and usage of online health platforms. Please identify how much you disagree or agree with each statement.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Important people in my life (family, friends, colleagues) who influence my behaviour, think that I should use an online health platform	○	○	○	○	○	○	○

People who are important to me (family, friends, colleagues) think that I should use an online health platform	○	○	○	○	○	○	○
I use an online health platform because of the proportion of my friends, family and colleagues that use it	○	○	○	○	○	○	○

People I am associated with who use an online health platform gain important benefits for using it	○	○	○	○	○	○	○
Having a personal profile on an online health platform is considered a status symbol	○	○	○	○	○	○	○

Health care professionals would encourage me to use an online health platform	○	○	○	○	○	○	○

End of Block: Social influence to use an online health platform

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Start of Block: Perceived reciprocity

This section includes questions related to reasons for disclosure on online health platforms. Please identify how much you disagree or agree with each statement.

	strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
When others disclose personal health information online, I believe that they expect me to do the same	○	○	○	○	○	○	○

Other online users trust me to return the favour of sharing personal health information	○	○	○	○	○	○	○

I know that other users disclose personal health information online about themselves, so it is only fair to do the same	○	○	○	○	○	○	○

End of Block: Perceived reciprocity

Start of Block: privacy risk beliefs

This section includes questions related to privacy risk beliefs and usage of online platforms. Please identify how much you disagree or agree with each statement.

	strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
In general, it is risky to give my private information to others online	○	○	○	○	○	○	○

There is a high potential for loss associated with giving my personal information to others online	○	○	○	○	○	○	○
There is too much uncertainty associated with giving my personal information to others online	○	○	○	○	○	○	○

Providing others my private information online could involve many unexpected problems	○	○	○	○	○	○	○
I feel safe giving my private information to others online	○	○	○	○	○	○	○

End of Block: privacy risk beliefs

Start of Block: Health information privacy concern

This section includes questions related to your privacy concerns regarding your health information. In this section, the term *health care entities* refers to technology vendors that may request/collect information related to your physical and mental health. Please identify how much you disagree or agree with each statement.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
It usually bothers me when health care entities ask me for personal health information	○	○	○	○	○	○	○

I am concerned that when I give personal health information to a healthcare entity for some reason, that they might use the information for other reasons	○	○	○	○	○	○	○

It bothers me to give my personal health information to so many health care entities	○	○	○	○	○	○	○
It usually bothers me when I am not aware or knowledgeable about how my personal health information will be used by health care entities	○	○	○	○	○	○	○

It usually bothers me when I do not have control of personal health information that I provide to health care entities	○	○	○	○	○	○	○

I am concerned when control is lost or unwillingly reduced as a result of providing health care entities with my personal health information	○	○	○	○	○	○	○
When health care entities ask me for personal health information, I sometimes think twice before providing it	○	○	○	○	○	○	○

I am concerned that health care entities would sell my health personal health information in their computer databases to other health care entities or non-health related organisations	○	○	○	○	○	○	○

It is very important to me that I am aware and knowledgeable about how my personal health information will be used by health care entities	○	○	○	○	○	○	○

It usually bothers me when I do not have control or autonomy over decisions about how my personal health information is used, and shared by health care entities	○	○	○	○	○	○	○

I’m concerned that health care entities are collecting too much personal health information about me	○	○	○	○	○	○	○
It usually bothers me when health care entities seeking my health information do not disclose the way the data are processed and used	○	○	○	○	○	○	○

Protection and accuracy

	strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I am concerned that health care entities do not take enough steps to make sure that unauthorised people cannot access my personal health information in their computers	○	○	○	○	○	○	○

I am concerned that health care entities would share my personal health information with other health care entities without my authorisation	○	○	○	○	○	○	○

I am concerned that health care entities’ databases that contain my personal health information are not protected from unauthorised access	○	○	○	○	○	○	○

I am concerned that health care entities do not take enough steps to make sure that my personal health information in their files is accurate	○	○	○	○	○	○	○

I am concerned that health care entities do not devote enough time and effort to preventing unauthorised access to my personal health information	○	○	○	○	○	○	○

I am concerned that health care entities do not devote enough time and effort to verifying the accuracy of my personal information in their databases	○	○	○	○	○	○	○

I am concerned that health care entities do not have adequate procedures to correct errors in my personal health information	○	○	○	○	○	○	○

End of Block: Health information privacy concern

Start of Block: Health status

The next questions relate to your personal health, and information related to your health.

In general, how would you rate your overall health?

○ Poor

○ Fair

○ Good

○ Very good

○ Excellent

Do you have any chronic illnesses (asthma, diabetes, coronary heart disease, inflammatory bowel disease etc.)?

○ Yes

○ No

○ I don't know

○ Prefer not to say

Do you have any other conditions/illnesses that periodically impact your life?

○ Yes

○ No

○ Prefer not to say

Do you have any sensitive illnesses (any condition you feel is private or embarrassing)?

○ Yes

○ No

○ Prefer not to say

End of Block: Health status

Start of Block: Personality

Here are a number of personality traits that may or may not apply to you. Please identify how much you disagree or agree with each statement. You should rate the extent to which the pair of traits applies to you, even if one characteristic applies more strongly than the other.

I see myself as:

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Extraverted, enthusiastic	○	○	○	○	○	○	○
Critical, quarrelsome	○	○	○	○	○	○	○
Dependable, self-disciplined	○	○	○	○	○	○	○
Anxious, easily upset	○	○	○	○	○	○	○
Open to new experiences, complex	○	○	○	○	○	○	○

Reserved, quiet	○	○	○	○	○	○	○
Sympathetic, warm	○	○	○	○	○	○	○
Disorganized, careless	○	○	○	○	○	○	○
Calm, emotionally stable	○	○	○	○	○	○	○
Conventional, uncreative	○	○	○	○	○	○	○

End of Block: Personality

Start of Block: Technology adoption

Online health platforms include any website or smartphone application that allows you to seek and store personal health information about pregnancy, medication management, mental health, fitness, diet, sleep, chronic illness, (WebMD, FitBit or

Apple Health for example).

Please identify how much you disagree or agree with each statement.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I intend to use/continue to use health technologies	○	○	○	○	○	○	○
I plan to use/ continue to use health technologies	○	○	○	○	○	○	○
I predict I will use/ continue to use health technologies	○	○	○	○	○	○	○

Please select the option that indicates how often you engage in the following activity

	Never	Once a month	2-3 times a month	1-3 times a week	4 times a week / every day
I use online health platforms	○	○	○	○	○

End of Block: Technology adoption

Start of Block: Demographics

Gender

○ Male

○ Female

○ Other

Age

○ 18-19

○ 20-24

○ 25-29

○ 30-34

○ 35-39

○ 40-44

○ 45-49

○ 50-54

○ 55-59

○ 60-64

○ 65-69

○ 70+

What is the highest level of education you have achieved to date?

○ Some high school or less

○ Completed high school

○ Some college undergraduate / Bachelor’s degree

○ Master’s degree / Graduate school

○ Beyond Masters

Which option best describes your current employment status?

○ Student

○ Jobseeker

○ Employed / Self-employed

○ Homemaker

○ Retired

Which industry best describes the one you are currently employed in? **(Employed only)**

○ Retail trade

○ Finance, insurance, real estate

○ Professional, scientific, and management services

○ Education

○ Healthcare and/or social services

○ Other, please specify:
____

Which discipline best describes the one you study? **(Students only)**

○ Arts and Humanities (e.g. History, Philosophy)
○ Business (e.g. Accounting, HRM)
○ Education
○ Engineering (e.g. Mechanical, Electrical)
○ Law
○ Life, Physical, or Mathematical Sciences
○ Medicine and Health Sciences (e.g. Nursing)
○ Social and Behavioural Sciences (Psychology, Sociology)
○ Computer Science
○ Other, please specify:
____

Please use this space to make any additional comments regarding digital health platforms, the survey, or your online self-disclosures

____

If you are interested in the follow up interview please enter you email
(if you have not already included it):

____

End of Block: Demographics

APPENDIX D: SURVEY ITEMS

Self-Disclosure

SPSS Code	Self-Disclosure – Amount
selfDisclosure_amount1	I often discuss my feelings about my health online
selfDisclosure_amount2	I usually discuss my health for fairly long periods at a time online
selfDisclosure_amount3	I spend little or no time discussing my own health online (Reversed)
selfDisclosure_amount4	I often discuss my health online

SPSS Code	Self-Disclosure – Depth
selfDisclosure_depth1	I intimately disclose who I really am, openly and fully in my interactions about my health online

selfDisclosure_depth2	I often disclose intimate, personal things about my health without hesitation online
selfDisclosure_depth3	I feel that I sometimes do not control my self-disclosure of personal health information online
selfDisclosure_depth4	Once I get started, I intimately and fully reveal personal health information in my self-disclosures online

SPSS Code	**Self-Disclosure – Honesty**
selfDisclosure_honesty1	I always feel completely sincere when I reveal my own feelings and experiences about my health online
selfDisclosure_honesty2	My online self-disclosures about my health are completely accurate reflections of how my health really is
selfDisclosure_honesty3	My statements online about my own feelings, emotions, and experiences relating to my health are always accurate self-perceptions
selfDisclosure_honesty4	I am always honest in my self-disclosures relating to my health online

SPSS Code	Self-Disclosure - Valence
selfDisclosure_valence1	I usually disclose positive things about my health online
selfDisclosure_valence2	I normally express my “good” feelings about my health online
selfDisclosure_valence3	Overall, my disclosures about my health online are more positive than negative

SPSS Code	Self-Disclosure - Intent
selfDisclosure_intent1	When I express my personal feelings relating to my health online, I am always aware of what I am doing and saying
selfDisclosure_intent2	When I reveal my feelings about my health online, I consciously intend to do so
selfDisclosure_intent3	When I am self-disclosing my health information online, I am consciously aware of what I am revealing

Trust in Platforms

	Trust –Technology Vendors

SPSS Code	
trustPlatform_vendors1	I think technology vendors are always honest when it comes to using my health information
trustPlatform_vendors2	I think technology vendors care about customers
trustPlatform_vendors3	I think technology vendors are opportunistic when using my health information
trustPlatform_vendors4	I think technology vendors are predictable and consistent with regards to using my health information
trustPlatform_vendors5	I think technology vendors are competent and effective in providing their services
trustPlatform_vendors6	I trust that technology vendors keep my best interests in mind when dealing with my health information
trustPlatform_vendors7	It would be risky to disclose my personal health information to technology vendors
trustPlatform_vendors8	There would be high potential for loss associated with disclosing my personal health information to technology vendors
trustPlatform_vendors9	There would be too much uncertainty associated with giving my personal health information to technology vendors
trustPlatform_vendors10	Providing technology vendors with my personal health information would involve many unexpected problems

SPSS Code	**Trust - Design**
trustPlatform_design1	I trust online health platforms with an intuitive layout
trustPlatform_design2	I trust online health platforms that are clear and easy to navigate

trustPlatform_design3	An online health platform with an intuitive layout would make it easier for me to share information

SPSS Code	**Trust - Perceived Reputation**
trustPlatform_perceivedReputation1	I trust health technology vendors with a .org domain
trustPlatform_perceivedReputation2	I trust health technology vendors with a .com domain
trustPlatform_perceivedReputation3	I trust health technology vendors with a .edu domain
trustPlatform_perceivedReputation4	I trust health technology vendors with a .gov domain
trustPlatform_perceivedReputation5	I trust health technology vendors with a .io domain

SPSS Code	**Trust - Information Quality**
trustPlatform_infoQuality1	I trust online health platforms that provide regular information updates
trustPlatform_infoQuality2	I trust online health platforms that provide clear and consistent messaging
trustPlatform_infoQuality3	I trust online health platforms that provide professional certification (ex. medical board certification)

Social Influence

SPSS Code	Social Influence
socialInfluence_1	Important people in my life (family, friends, colleagues) who influence my behaviour, think that I should use an online health platform

socialInfluence_2	People who are important to me (family, friends, colleagues) think that I should use an online health platform
socialInfluence_3	I use an online health platform because of the proportion of my friends, family and colleagues that use it
socialInfluence_4	People I am associated with who use an online health platform gain important benefits for using it
socialInfluence_5	Having a personal profile on an online health platform is considered a status symbol
socialInfluence_6	Health care professionals would encourage me to use an online health platform

Perceived Reciprocity

SPSS Code	**Perceived Reciprocity**
perceivedReciprocity_1	When others disclose personal health information online, I believe that they expect me to do the same
perceivedReciprocity_2	Other online users trust me to return the favour of sharing personal health information
perceivedReciprocity_3	I know that other users disclose personal health information online about themselves, so it is only fair to do the same

Risk Beliefs

SPSS Code	Risk Beliefs
perceivedRiskBeliefs_1	In general, it is risky to give my private information to others online
perceivedRiskBeliefs_2	There is a high potential for loss associated with giving my personal information to others online
perceivedRiskBeliefs_3	There is too much uncertainty associated with giving my personal information to others online
perceivedRiskBeliefs_4	Providing others my private information online could involve many unexpected problems
perceivedRiskBeliefs_5	I feel safe giving my private information to others online

Health Information Privacy Concerns

Collection and use	
HIPC_collectionUse_1	It usually bothers me when health care entities ask me for personal health information
HIPC_collectionUse_2	I am concerned that when I give personal health information to a healthcare entity for some reason, that they might use the information for other reasons
HIPC_collectionUse_3	It bothers me to give my personal health information to so many health care entities
HIPC_collectionUse_4	It usually bothers me when I am not aware or knowledgeable about how my personal health information will be used by health care entities
HIPC_collectionUse_5	It usually bothers me when I do not have control of personal health information that I provide to health care entities
HIPC_collectionUse_6	I am concerned when control is lost or unwillingly reduced as a result of providing health care entities with my personal health information
HIPC_collectionUse_7	When health care entities ask me for personal health information, I sometimes think twice before providing it
HIPC_collectionUse_8	I am concerned that health care entities would sell my health personal health information in their computer databases to other health care entities or non-health related organisations

HIPC_collectionUse_9	It is very important to me that I am aware and knowledgeable about how my personal health information will be used by health care entities
HIPC_collectionUse_10	It usually bothers me when I do not have control or autonomy over decisions about how my personal health information is used, and shared by health care entities
HIPC_collectionUse_11	I'm concerned that health care entities are collecting too much personal health information about me
HIPC_collectionUse_12	It usually bothers me when health care entities seeking my health information do not disclose the way the data are processed and used

SPSS code	**Protection and accuracy**
HIPC_protectionAccuracy_1	I am concerned that health care entities do not take enough steps to make sure that unauthorised people cannot access my personal health information in their computers
HIPC_protectionAccuracy_2	I am concerned that health care entities would share my personal health information with other health care entities without my authorisation

HIPC_protectionAccuracy_3	I am concerned that health care entities' databases that contain my personal health information are not protected from unauthorised access
HIPC_protectionAccuracy_4	I am concerned that health care entities do not take enough steps to make sure that my personal health information in their files is accurate
HIPC_protectionAccuracy_5	I am concerned that health care entities do not devote enough time and effort to preventing unauthorised access to my personal health information
HIPC_protectionAccuracy_6	I am concerned that health care entities do not devote enough time and effort to verifying the accuracy of my personal information in their databases
HIPC_protectionAccuracy_7	I am concerned that health care entities do not have adequate procedures to correct errors in my personal health information

Health Status

	Health Status
HealthStatus	In general, how would you rate your overall health?

Chronic_illness	Do you have any chronic illnesses (asthma, diabetes, coronary heart disease, inflammatory bowel disease etc.)?
Periodic_illness	Do you have any other conditions/illnesses that periodically impact your life?
Sensitive_illness	Do you have any sensitive illnesses (any condition you feel is private or embarrassing)?

Personality

SPSS Code	**Extroverted**
personality_extroverted	Extraverted, enthusiastic
personality__introvert	Reserved, quiet

SPSS Code	**Agreeable**
personality__agreeable	Sympathetic, warm

personality_notAgreeable	Critical, quarrelsome

SPSS Code	Conscientious
personality_conscientious	Dependable, self-disciplined
personality_notAgreeable	Disorganized, careless

SPSS Code	Neurotic
personality_neurotic	Anxious, easily upset
personality_notNeurotic	Calm, emotionally stable

	Open

SPSS Code	
personality_open	Open to new experiences, complex
personality_notOpen	Conventional, uncreative

Demographics

SPSS Code	**Age**
Age	18-19, 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-64, 65-69, 70+

SPSS Code	**Gender**
Gender	Male, Female, Other

	Education (Ireland)	**Education (USA)**

SPSS Code		
Education	Some secondary school or less; Completed secondary school; Some college undergraduate / Bachelor’s degree; Master’s degree; Beyond Masters.	Some high school or less; Completed high school; Some college undergraduate / Bachelor’s degree; Master’s degree / Graduate school; Beyond Masters.

SPSS Code	**Employment Status**
Employment	Student; Jobseeker; Employed/Self-Employed; Homemaker; Retired

SPSS Code	**Employment Status**
Employment	Student; Jobseeker; Employed/Self-Employed; Homemaker; Retired

APPENDIX E: INTERVIEW CONSENT FORM AND INTERVIEW GUIDE

Arizona State University & Dublin City University (Ireland)

Consent Form for Research Interview

Protocol title: An examination of the antecedents of citizen self-disclosure on online health platform**s**

Researcher: Eoghan Mc Conalogue (PhD candidate), Assistant Professor at Dublin City University (Ireland)

Purpose of the study: You are invited to participate in a PhD Study conducted by Eoghan Mc Conalogue, Dublin City University in Ireland. This research is supported by the ASU-DCU Transatlantic Partnership and the HEA Mobility fund.

This study explores citizens' behaviours related to the online self-disclosure of information pertaining to their physical and mental health. Participants are invited to participate in a one to one interview with the researcher to discuss their experiences and perspectives regarding self-disclosure of health information online.

Procedure: Today, you will answer some questions related to how you share personal health information online.

The interview will last approximately 30 minutes. The researcher will request to record (audio only) the interview.

You can quit at any time. If you quit, you will not answer any more questions. We will ask you if we can use the answers you already gave.

Possible Risks or Discomforts: You may feel anxiety, stress, or irritation while answering the questions relating to your health status. The researcher will be here to reduce this risk. The researcher can answer any questions you have.

There is risk of loss of privacy as we will record your voice. To minimize privacy risks, we protect the data that you provide.

There is no direct risk of physical injury from being in this study.

Possible Benefits: You may not directly benefit from this study. The results may help learn what health data you want to protect. The results of the study may help others.

Financial information: The study does not cost you anything.

Rights as a Research Participant: You have the right to stop the study at any time. Your choices will be respected. You will not lose any benefits if you do not participate in the study.

Privacy: Results of this study may be used for teaching, research, publications, and presentations. Your identity will be protected. Your answers will be saved to a number instead of your name. The audio recordings will be locked up in the researcher's office. The audio recordings will be destroyed once transcribed.

Questions: If you have questions, please contact Eoghan Mc Conalogue at +353 85 1725779 or eoghan.mcconalogue@dcu.ie

If you have questions about your rights as a research participant or think you are at a risk, contact the ASU Institutional Review Board at (480) 965-6788.

Statement of Consent: I am 18 years old or older. I am willing to take part in the study. I understand that Arizona State University & Dublin City University researchers want to collect data. The study aims to understand citizens' behaviours related to the online self-disclosure of information pertaining to their physical and mental health. I understand that will be an audio recording of this interview. The study should take approximately 30 minutes.

Your signature below documents your permission to take part in this research.

Participant – please complete the following (Circle Yes or No for each question)

I have read the Plain Language Statement (or had it read to me)

Yes/No

I understand the information provided

Yes/No

I have had an opportunity to ask questions and discuss this study

Yes/No

I have received satisfactory answers to all my questions

Yes/No

I agree to participate in an interview with the researcher

Yes/No

I am aware that my interview will be audiotaped

Yes/No

I am aware that I may withdraw from the Research Study at any point

Yes/No

I understand that my participation will be anonymous

Yes/No

The information you provide in the interview will be confidential and stored securely in the researcher's office. This information will be securely disposed of after transcription.

I have read and understood the information in this form. My questions and concerns have been answered by the researchers, and I have a copy of this consent form. Therefore, I consent to take part in this research project

Participants Signature:

____

Name in Block Capitals:

____

Signature of person obtaining consent:

____

Printed name of person obtaining consent:

____

Date: ______________________________________

Introduction

[Aim: Thank participant, explain interview process, and allow for questions].

Firstly, I want to say thank you for taking the time to meet with me today. Before we get started, I will tell you a bit about what we’re doing today.

The interview will consist of broad questions and topics all related to your sharing of personal health information online. If you are unsure of any terms, I will clarify them.

There are no right or wrong answers, I am just looking for your personal opinion and you do not have to share any personal health conditions, but if you do that will be confidential.

If it is okay with you, I will audio record the interview on this device. The interview is completely confidential; your name or information will never be used. The audio recording of the interview will be locked in my office. After I transcribe the audio file, it will be deleted.

If you would rather not answer a question or want to stop at any time that's completely fine. The interview should last approximately 30 minutes. Have you any questions before we start?

Participant Background

Are you employed / student / retired?

[Employed/Self-employed] Q: To start, could you tell me about your job, what do you do for a living?

[Students] Q: Could you tell me about your studies? (Discipline, year, part-time jobs)

[Retirees] Q: Prior to retiring, what did you do for living? (How long are you retired?)

Internet Experience

Broad Introduction Question: Tell me about your Technology Use? (length of experience with computers, types of devices used, frequency of use, different purposes)

Internet Q: Tell me about your Internet Use (frequency of use, purposes, devices used, experience)

Additional Qs: [Employees] Would you use computers much in work? (types of uses, access to personal data?)

[Retirees] Q: Are there any things you can't/won't do online (ascertain limits in ability and desire)

Self-disclosure of personal health information behaviours

Broad Introduction Question: What do you understand personal health information to be? (EHR data / data they generate.) (Examples from: pregnancy, medication management, mental health, fitness, diet, sleep, chronic illness based application

Do you disclose personal health information online?

For what purposes (ascertain if fitness related, related to specific condition or generic disclosures)

How often would you disclose personal health information online?

To what degree do you disclose personal health information online? (depth and frequency)

With what intent do you disclose personal health information online?

Are you honest in your disclosures?

Are there any particular websites you use for health information disclosure? (Why?)

Additional Qs: What devices do you use?

Do you visit health forums? (Browse or post)

Social media activity (to determine frequency of information disclosure)

Health IT Experience

Broad Introduction Question: Do you use any mobile health applications such as FitBit or WebMD (explain the term: websites or applications on a smartphone that allow you to seek and store personal health information about pregnancy, medication management, mental health, fitness, diet, sleep, chronic illness)

Have you ever used a mobile health application? (If so, details on the application, reason for cessation of use)

Do you use any wearable tracking devices (explain the term: devices, such as a smartphone, or FitBit watch that save data about you automatically (steps walked) without your manual input)?

Additional Qs: (Retirees) Have you heard of these applications (Describe if possible)

Use/Awareness of Healthkit on iPhone

Would you use mobile health applications/wearable devices? (Reasons why/why not, what type of applications)

Antecedents

Trust: Technology vendors

Broad Introductory Question: How would you describe your trust in technology companies with your personal health information (Why?)

How would you describe your trust in them to protect your personal health information?

Additional Qs: Small vs. large technology organisations

Trust in ability to protect health data (Competence)

Trust: design

What role does the design of health platforms play in your health disclosures? (ease of use)

Trust: reputation

Does domain registration influence your decision to trust a health platform?

Trust: information quality

To what degree does the quality of information provided by a health platform impact your perceived trustworthiness of the platform? (grammatical errors / objectivity / regular updates)

Social influence to use online health platforms

Do people close to you encourage you to use online health platforms / apps?

Do people close to you use online health platforms?

Do people close to you get benefit from using online health platforms? What benefits?

Do you feel having a profile on an online health platform could be considered a status symbol?

Perceived reciprocity

When others disclosure personal information online, do you think they expect the same form you?

Do others trust that you will share personal information online, if they have?

Is it only fair that you share personal data online because others have done so?

Perceived risk beliefs

Do you think it is a risk to share personal data online? (what are those risks?)

Do you think there is a high potential for loss associated with giving personal information to others online? (what uncertainties exist?)

Do you ever feel safe sharing personal information online?

Health Information Privacy Concerns

How would you describe your concern for the privacy of your health data? (Any current concerns, past concerns)

What are currently concerned about? (health professionals and technology companies)

Collection: How do you feel about the collection and storage of large quantities of your health data? (what data types, health professionals and technology companies, present vs. future concern)

Secondary Use: Are you ever concerned that your health data might be used for secondary purposes (explain term: advertising campaign, profiling, purposes for which you are not aware) without your permission? (health professionals and technology companies, present vs. future concern, what uses)

Additional: What purposes do you think your health data should be used for? (health professionals and technology companies, conditions on use)

Improper Access: Are you ever concerned that your health data might be accessed by unauthorised parties? (health professionals and technology companies, present vs. future concern, what parties, why)

Additional: What parties do you think should have access to your health data (health professionals, employers, legal and insurance companies, government etc., why)

Errors: Does the possibility of errors in your health data cause concern? (Why, health professionals and technology companies, present vs. future concern)

Control: Do you currently believe you have control over your health data (health professionals and technology companies, why, how do you feel, present vs. future concern)

Additional: What level of control over your health data do you think you should have? (health professionals and technology vendors)

Awareness: Are you currently aware of how your health data is protected? (health professionals and technology companies, present vs. future concern)

Are you aware of how your health data is used and shared? health professionals and technology companies, present vs. future concern)

Additional: Is awareness important for you? Should we be more aware? Should we ask more questions/should health professionals/technology companies be more transparent?

Additional Questions: Is privacy (health data) important to you? Why?

Health Status

How would you rate your health? (poor, fair,good, very good, excellent)

Do you have any illness that impacts your life? (yes/no/prefer not to say)

Personality

Would you describe yourself as Open, Conscientious, Extrovert, Agreeable or Neurotic? (Place in order 1-5,1 being most)

> *Open: someone who is open to new experiences. A creative and curious person.*
>
> *Conscientious: A tendency to be organized and dependable. Self-disciplined.*
>
> *Extrovert: A sociable, outgoing person, energetic and generally positive.*
>
> *Agreeable: A friendly and compassionate person. Cooperative.*
>
> *Neurotic: A sensitive or nervous person. Prone to anxiety or emotional instability*

Health Information Technologies

Mobile Health

We previously discussed mobile health applications; if you are not already a user of mobile health applications would you use these technologies? (Which ones, why, conditions)

What technologies would you not use? (Why)

What do you think the benefits of these technologies are?

If your friend, family member, or doctor recommended one of these technologies would you adopt? (Social Influence) [Retirees] Do you think you could use these technologies? (self-efficacy)

Close

Any additional comments? Any questions?

[Clarify any confusing comments at this point if necessary]

Thank you so much for taking the time to meet with me today

APPENDIX F: SAMPLE INTERVIEW CODING PROTOCOL

	Themes	**Codes**	**Sub-codes**
Antecedents	Trust	1. Vendors 2. Professionals 3. Design 4. Reputation 5. Info Quality	Competence Benevolence Integrity
	Privacy Risk beliefs	Personal risks	Perception of Risk Potential for loss Safe online
	Social influence	Encouragement Benefits	Encouragement from family and friends Status symbol Encouragement form Health Pros.
	Perceived Reciprocity	1.Expected 2. Not expected	Expectation belief

			Trusting expectations of others Fair
	HIPC	1. Collection 2. Secondary Use 3. Improper Access 4. Errors 5. Control 6. Awareness	Broad concerns Current vs. Future concerns Health professionals vs. technology vendors Blind assumptions of privacy
	Personality	1. Open 2. Conscientious 3. Extrovert 4. Agreeableness 5. Neurotic	-
Dimensions of self-disclosure	Self-disclosure of personal health information behaviours	1. Amount 2. Depth 3. Honesty 4. Intent 5. Valence	Intimacy Personal withdraw
Additional factors	Health status	-	Chronic Sensitive Periodic