QoS-based Experience-aware Adaptation in Multimedia e-Learning - A Learner, is a Learner, is a User, is a Customer

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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 Doctor of Philosophy (Ph.D.) is entirely my own work, 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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List of Publications

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Scotton, J., **Moebs, S.**, McManis,J., Cristea, A.I. (2009) "A Case Study on Merging Strategies for Authoring QoE-based Adaptive Hypermedia" Proceedings ECTEL - A3H: 7th International Workshop on Authoring of Adaptive and Adaptable Hypermedia, Nice, France

Trapp, S., Thomas, L., **Möbs, S.** (2009) "Tailoring Technology-Enhanced Learning Arrangements to Individual Needs" International Journal of Advanced Corporate Learning, Vol. 2 No. 2, p. 40-45

Kilbane, B., **Moebs, S.**, McManis, J. (2009) "Learning Styles or Not? A Classroom Experience" Proceedings Irish Educational Technology Users' Conference (EdTech), Dublin, Ireland

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Abstract

One of the challenges for the future of technology-enhanced learning is the retention of learners. On-line learning environments should engage learners and provide an appropriate "Quality of Experience" (QoE). For more than a decade, adaptive hypermedia systems have been used to adapt content and instruction to individual knowledge, goals and preferences in an effort to engage learners. However, even if the content is highly engaging it can be very difficult to achieve good Quality of Experience for people without sufficient technological infrastructure or fixed access, such as in rural or remote areas and learners in developing economies. Despite recent improvements in network technology, any increases in bandwidth are quickly consumed by more demanding applications.

So far QoE has been approached primarily from an engineering perspective, considering technical factors such as download times or video quality. But arguably QoE in multimedia e-learning systems must be viewed in a broader sense and has to be aligned with the concept of user experience to capture more dimensions of the experience.

In this context this thesis proposes a new model for QoE in adaptive multimedia e-learning, combining QoS, learning theory and flow experience. The proposed adaptation policies for QoE combine multimedia e-learning theory with network QoS adaptations. A novel measurement model for QoE in adaptive multimedia e-learning was developed to measure QoE and the factors influencing QoE and to explore the inter-relationship of various aspects of QoE.

This research identified learning and flow experience as key contributors to QoE in multimedia e-learning systems. Moreover, the results indicate that an international Delphi expert study under-estimated the impact of Quality of Service on QoE in multimedia e-learning; the research reported in this thesis, including network simulations and extensive user tests, showed that the impact of QoS deserves more consideration. The proposed QAMM2 algorithm combining QoS adaptation and media mix adaptation was the subject of simulation and extensive user testing which demonstrated that QoE in multimedia e-learning systems can indeed be improved by adjusting the content media format to suit network conditions.

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List of Abbreviations

AH	Adaptive Hypermedia
AHA!	Adaptive hypermedia Architecture
AHS	Adaptive Hypermedia System
AICC	Aviation Industry Computer-Based Training Committee
ALS	Adaptive Learning Spaces
APeLS	Adaptive Personalized e-Learning Service
BW	Bandwidth
CBR	Constant Bit Rate
CLE	Collaboration and Learning Environment
CMS	Content Management System
DSL	Digital Subscriber Line
EFL	English as a Foreign Language
ESM	Experience sampling method
FMM	Fixed Media Mix
GNU	GNU's Not Unix
GUI	Graphical User Interface
HAM	Hypertext Abstract Machine
ICT	Information and Communication Technology
IEC	International Electrotechnical Commission
IELTS	International English Language Testing System
ISO	International Organisation for Standardisation
ITU	International Telecommunication Union
LAG	three layers adaptation granularity
LMS	Learning Management System
LOM	Learning Object Metadata

LUCie	Learner, User, Customer in e-learning
Moodle	Modular Object-Oriented Dynamic Learning Environment
NS-2	Network Simulator 2
OCL	Object Constraint Language
OTcl	MIT Object Tcl
P-A-T	Person-Artefact-Task
PBL	Problem Based Learning
PrEmo	Product Emotion
PSNR	Peak Signal-to-Noise Ratio
QAMM	Quality Adaptation for Media Mix
QoCE	Quality of Customer Experience
QoE	Quality of Experience
QoP	Quality of Perception
QoS	Quality of Service
QoUE	Quality of User Experience
RDF	Resource Description Framework
RSS	RDF Site Summary
RTF	Rich Text Format
SCORM	Sharable Content Object Reference model
SD	Standard Deviation
SEM	Structural Equation Modelling
SMIL	Synchronized Multimedia Integration Language
SURGE	Scalable URL Reference Generator
Tcl	Tool command language
UML	Unified Modeling Language
UX	User Experience
VARK	Visual- Aural-Read/Write-Kinesthetic
VBR	Variable Bit Rate
VFM	virtual course flow measure
VoIP	Voice over IP
WLAN	Wireless Local Area Network
XAHM	XML-based Adaptive Hypermedia Model
XML	Extensible Markup Language

1 Introduction

1.1 Research Motivation

Despite the current economic downturn, analysts expect an increase in e-learning [139]. A recent study on e-learning in Europe [60] points out future trends in technology-enhanced learning. Provision of suitable services for people without sufficient technical infrastructure and fixed access, in rural or remote areas and learners in developing economies is one of the first trends mentioned in the study under the headline of persuasive technologies. For these people, network conditions vary strongly despite efforts to improve broadband capacity and coverage. However, even with comprehensive broadband connection the race between improved infrastructure and increasing demands from new applications is bound to continue [115] [180].

Against the background of these issues the retention of learners or learner engagement is one of the challenges for the future of technology-enhanced learning. Learner engagement is key to retention. Figure 1 summarises the main factors influencing learner engagement in technology-enhanced learning.

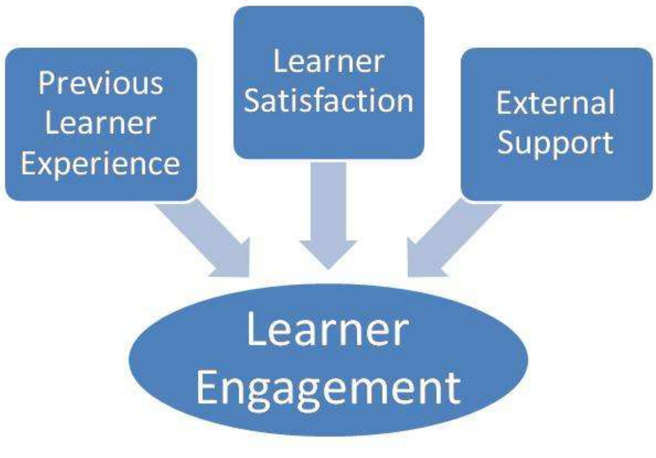

Figure 1: Factors of Learner Engagement

The experience of the learner determines learning results as well as drop-out rates and retention in e-learning. As Levy [137] has pointed out, learner satisfaction is the key indicator for drop-out in e-learning. Levy also found, that this holds true independent of the learner's locus of control; from externally to internally motivated learners, satisfaction with the learning experience appears to be crucial.

These results have been confirmed by Park and Choi [174] in a recent study, which concludes that enhanced learner satisfaction together with external support can improve the retention rates and learner engagement. Learner engagement is linked with Quality of Experience (QoE), through learner satisfaction, which can be summarized as the combination of flow experience and learning outcome.

Recent efforts to increase flow experience include the use of web services, educational games and multimedia. Delivery systems and media formats have been identified as major research trends in technology-enhanced learning (TEL) [149]. Quality of Experience in technology-enhanced learning is often mentioned in the same context as Quality of Service (QoS) or Quality of Perception (QoP) [98] [78]. While Quality of Service describes objective technical parameters of multimedia and network conditions, Quality of Perception considers how a user perceives technically defined quality levels [75], for example in a video. Quality of Experience considerations go one step further and aim to also capture relevance of context and user expectation [119]. All these concepts focus on the impact of technical conditions on user satisfaction. However, a mix of different media has been identified as another key contributor to learner motivation [211].

Adaptive hypermedia systems have been used to adjust content to individuals in an effort to engage learners more effectively. The following scenario demonstrates the need for an adaptation combining Quality of Service and media mix considerations for a good Quality of Experience from the learner's perspective.

Father Ted lives on the remote Craggy Island off the west coast of Ireland. He has decided he needs to learn German to keep up with current changes in senior management in Rome, but access to face-to-face classes in higher education or professional training from a remote island is very difficult if not impossible. So he signs up for an on-line class. Although he does not have the most stable and powerful Internet connection, he still enjoys the course. The course provides a mix of different materials and a variety of videos, audio clips or illustrated text. Materials are easy to access at all times and he enjoys the course so much, he often finds himself spending more time than he originally planned and his learning shows good progress.

On a trip to a meeting he runs into a colleague who lives in Dublin, who has an excellent broadband connection, and who also signed up for the course. They are very surprised when they compare their experiences and realize that they both learned the same amount, found the course equally enjoyable, but were not necessarily presented with identical material. Father Ted cannot remember all of the videos his colleague mentions, but he on the other hand recalls some very interesting audio clips his colleague seemed to have missed. Nevertheless they both enjoyed the course a lot, because:

- they both reached their learning goals.
- they did not run into problems with excessively long download times of material.

Technology-enhanced learning is providing educational access to diverse populations in remote locations that in the past would not have been reachable. However, even if the content is highly engaging it can be very difficult to achieve good Quality of Experience for people without sufficient technological infrastructure or fixed access. Despite powerful communication networks increasingly reaching these remote places, the race between infrastructure and resource-demanding applications remains [145]. This competition can leave learners anywhere, but particularly in rural areas 0 with insufficient network resources, resulting in an unsatisfactory experience regardless of the efforts to create an engaging learning experience.

In this setting we discuss Quality of Experience (QoE) and the factors that impact the QoE of on-line learners. A QoE model is proposed that considers the impact of QoS on flow experience and learning, which then in turn impact the Quality of Experience (see Figure 2).

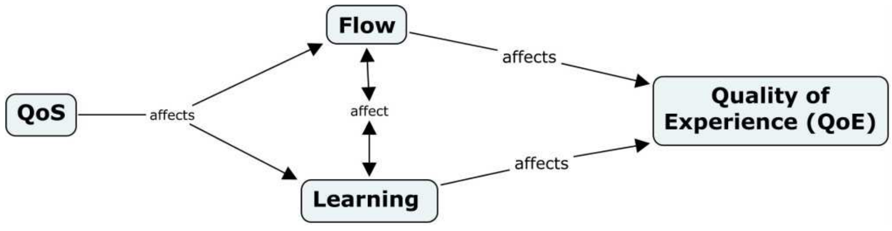

Figure 2: Proposed QoE Model

The QoE model considers three roles of the learner: learner, user and customer. The learner does not always take on all these roles simultaneously, but they all affect the Quality of Experience. Learning-related factors have an impact on the role of the learner, QoS strongly affects the user, and the customer is influenced by flow experience.

The focus of this research is the investigation of QoE improvement through an adaptation that combines Quality of Service (QoS) information with a learning theoretical approach and the psychological concept of the flow experience, serving the three roles of the learner.

This research aims to contribute to the area of technology-enhanced learning by taking QoS conditions in consideration for the selection of suitable learning materials. It makes learning systems more accessible, including those learner groups with weak internet connections and will afford them a more positive learning experience.

1.2 Problem and Solution

Problem The drop-out rate in technology-enhanced learning is high. Instructional designers add more demanding media to the mix of learning materials to conquer this effect. However, an enhanced mix of learning materials requires excellent network delivery conditions. This quality level of network conditions is not guaranteed everywhere at all times and as a result materials are delivered in low quality setting, increasing the potential drop-out rate of learners.

Solution The proposed solution enables a media mix conducive to the flow experience and harmonizes media selection and network conditions. This thesis presents the Quality-Adaptation for Media Mix (QAMM) algorithm which combines consideration of network conditions and learning theoretical aspects for the selection of learning materials.

1.3 Contributions

This thesis contributes to the state of the art in the area of technology-enhanced learning by introducing three novel aspects.

- Model for Quality of Experience in multimedia e-learning

The model brings together engineering, psychological and learning concepts for QoE in e-learning. In contrast to previous work it harmonizes the technically-oriented concept of Quality of Experience and the concept of user experience, which is rooted in the human-computer-interaction context. The combined consideration of QoS, multimedia learning theory and flow experience allows for a holistic concept of Quality of Experience (QoE) in adaptive hypermedia systems.

- Adaptation policies for Quality of Experience in multimedia e-learning.

The adaptation policies consider available bandwidth and previously used media. This small set of selection criteria allows embedding the policies in existing adaptation algorithms.

- Measurement model for Quality of Experience in multimedia e-learning

The measurement model identifies a valid set of parameters to define the quality of experience in an adaptive hypermedia e-learning system and reflects the holistic concept of the QoE model.

1.4 Short Outline of the Thesis

The remainder of this thesis is structured as follows.

Chapter 2 presents the mixed-method research methodology of this research and gives an overview of how the parts of the research are connected.

Chapter 3 provides an overview of important works related to this thesis. The literature review considers learning technologies, adaptive hypermedia, Quality of Service, flow experience and Quality of Experience.

The proposed QoE model, including adaptation policies and QoE parameters and measurement are introduced in chapter 4.

The next three chapters present the main parts of this research. Chapter 5 presents an international Delphi study investigating a list of hypotheses developed from the related work presented in chapter 3. Chapter 6 describes network simulations of the proposed algorithm. User testing combines results from the literature review, the Delphi study and the simulations. The results and analysis are described in chapter 7.

Finally a summary of the main conclusions and contributions and some suggestions for future work are presented in chapter 8.

2 Research Methodology

2.1 Introduction

This research combines multimedia engineering and e-learning. Included in the e-learning part are learning theoretical and psychological aspects. The research design aims to reflect this in combining research methods from engineering and social sciences. It consists of 4 main parts, literature review, Delphi study, simulation and user testing (see Figure 3). These lead to the development of adaptation policies, which are later incorporated into a testing prototype.

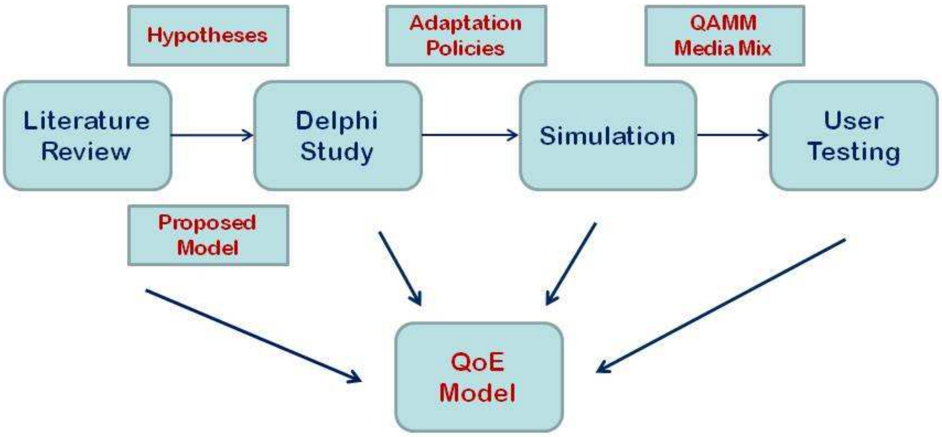

Figure 3: Research Methodology

The literature review fed into the Delphi study with a list of hypotheses. It also led to the initial proposed QoE model. The results of the Delphi study informed the development of adaptation policies, which were used for simulations and user testing. The simulations considered selected metrics and provided information about the media mix resulting from the different adaptation scenarios. The results of the simulation were then used to set the media mix applied for the different scenarios in user testing. Each step of the research fed into the refinement of the QoE model. A more detailed description of the research methodology is given in this chapter.

2.2 Literature Review

The literature review gives an overview over the background theories and related research in relation to the main focus of this research, the Quality of Experience of the learner. It introduces the main concepts, such as flow experience, Quality of Service and Quality of Experience. From the literature review and discussions at conferences the hypotheses for the Delphi study were drawn.

The literature review is presented as related work in chapter 3.

2.3 Delphi Study

The Delphi study is an accepted technique for gathering expert opinions on a topic [140]. The Delphi study investigated feedback from an expert panel on a list 17 of hypotheses derived from the initial literature review. It collected expert opinion on importance ranking and agreement level on the hypotheses. A pre-study with expert interviews validated the hypotheses drawn from the literature review, before a web-based Delphi study [3] was carried out. The Delphi study consisted of three rounds and involved 30 international experts from the research areas e-learning, multimedia engineering, user experience and psychology. The analysis of the results included content analysis and an approach for statistical analysis outlined in previous research [109] and the Delphi study literature [46] [35]. Chapter 5 presents the results of the Delphi study.

2.4 Development and Implementation of Prototype

The development of adaptation policies to enhance Quality of Experience is the main goal of this research. The policies describe the sequence of steps necessary to implement the QoE model outlined in chapter 4. The results of the Delphi study and the results of the literature review, including an existing QoE model [97], were the starting points for their development. The adaptation policies were implemented as an adaptivity prototype [189] for *AHA!* in the LAG language [39]. However, this adaptivity implementation was not used for testing, because the adaptive platform had too little of the "touch and feel" of a professional learning management system, which would have affected the user testing. For testing the *Moodle* platform was used. Although not able to provide adaptability, it provided an environment for a Wizard-of-Oz type study [122].

2.5 Network Simulation

The objective of the network simulations was to analyse the system behaviour when a learning session was performed in an environment with changing network conditions (see Figure 4).

The simulations had two goals:

- Investigate the impact on performance if QoS-adaptivity is applied
- Investigate the impact on performance if the combined QoS and Media Mix Adaptivity is applied

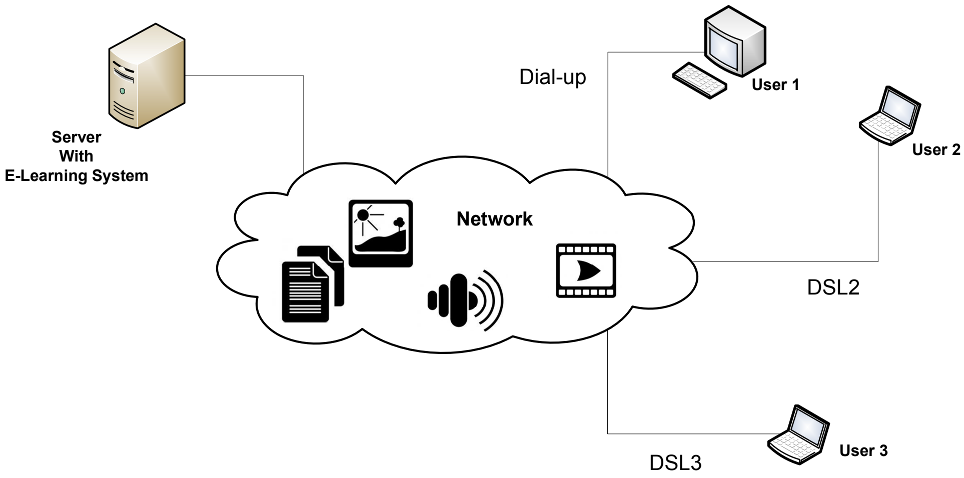

Figure 4: Simulation Environment

The results were then used for the setup of the media mix in user testing.

The metrics considered for the performance evaluation were startup delay and network usage. Success criteria targets are network usage as high as necessary to deliver with as small a startup delay as possible and an experience as varied as possible, without creating peaks for usage of network resources.

The simulations were performed using the Network simulator version 2 (NS-2) [164] and ElearnTraf, an extension of WebTraf, the web traffic model in NS-2. The results of the simulations will be presented in chapter 6.

2.6 User Testing

User tests were run at different stages of the project, testing the impact of the adaptation at different levels and for different aspects. Testing investigated the impact of the following on the learning experience:

1. Perceived quality of media and pedagogical approach
2. QoS-adaptive media
3. QoS-adaptive media mix

To get reliable and valid data, the test group used should include similar test persons. Quality of Experience based on QoS changes is hard to examine if the test group has e.g. widely varying motivation levels.

To ensure access to a comparable group of motivated users for user tests running over a longer period of time, cooperation with the on-campus language service was agreed. In addition the online course academic writing was promoted by the International Office and the Office for Graduate Research. The tests were run with adult students, aged between 20 and 40, with good computer literacy and basic to intermediate knowledge of the subject (EFL/Academic Writing). All the students were either attending intermediate to advanced English courses at DCU Language Service in preparation of postgraduate studies at DCU or postgraduate researchers from different faculties at DCU. The different user tests were not necessarily run with the same individuals, but with a comparable group.

To avoid creating too much of an artificial environment, the tests were run in one of the regular student laboratories.

Analysis and results of the user tests will be presented in chapter 7.

2.7 Summary of Research Methodology

The mixed-method research approach provides qualitative data from the Delphi study exploring initial hypotheses, while the experimental settings of simulations and user testing evaluate selected hypotheses from the Delphi study. The literature review provides the initial input for all three parts.

3 Related Work

3.1 Introduction

A learner is a learner, is a user, is a customer is the overarching theme of this work. This chapter gives a brief overview of the basic technologies and theories needed to come up with a model and an algorithm for an adaptive e-learning system aiming at improved Quality of Experience which considers the three roles of the learner. It therefore looks at:

- learning technologies
- adaptive hypermedia
- Quality of Service
- flow experience
- Quality of Experience.

The chapter starts with the section on learning technologies and gives an overview on learning theory and learning methods. The section on learning theories considers the role of the learner and is the basis for the following more technical topics. A sound learning background will help finding technological solutions that keep the learner in focus. The role of the user brings us to adaptive hypermedia (AH); this section looks at the basic architecture of AH and provides a comparison of adaptive and non-adaptive systems. As a customer the learner will have expectations on the application Quality of Service, which depends on the network QoS; the concept of network QoS is outlined by introducing four basic parameters, jitter, delay, loss and bandwidth. A captivating experience is an incentive for the user to return – the flow is introduced as a concept describing the optimal experience. The final section introduces Quality of Experience (QoE) and discusses related concepts and the relationship between QoE and User Experience (UX). The section on QoE combines all three roles, QoE being affected by expectations of learner, user and customer.

3.2 Learning Technologies

Learning technologies describe theories and methods to facilitate learning and consist of a number of different areas. This section outlines selected aspects of learning theory, different learning methods and a related psychological concept, the flow experience. Dewey's philosophy is chosen as a well accepted educational philosophy which caters for complex learning for learners with comparatively high learning abilities. Adult learners as a user group have different needs compared to younger learners. Knowles' learning theory introduces the concept of andragogy [129]. Learning Styles are concepts often used in adaptive learning systems. They are therefore briefly introduced and summarized, leading to the topics of motivation in e-learning and multimedia learning [5] [22]. Multimedia learning [150] [152] in combination with research on motivation in e-learning are introduced as concepts replacing learning styles used in other systems. Learning methods have been selected for their suitability in relation to learning theory, which in turn were chosen, because they seem to be most relevant for the task at hand, focusing on Quality of Experience of adult learners.

3.2.1 Learning Theory

Major learning theorists can be differentiated by their suitability for training, education or self-directed inquiry, which in turn can be described by two criteria, complexity of the learning task and level of individual learning ability (see Figure 5) [129]. My work aims to cater for education and self-directed inquiry learning.

Education is learning toward a broader perspective, like becoming an innovative engineer or a creative artist. Self-directed inquiry learning was developed as a concept mainly based on Dewey's ideas [51]. Dewey is also known as one of the founders of constructivism and his theory connects teaching and self-directed inquiry learning.

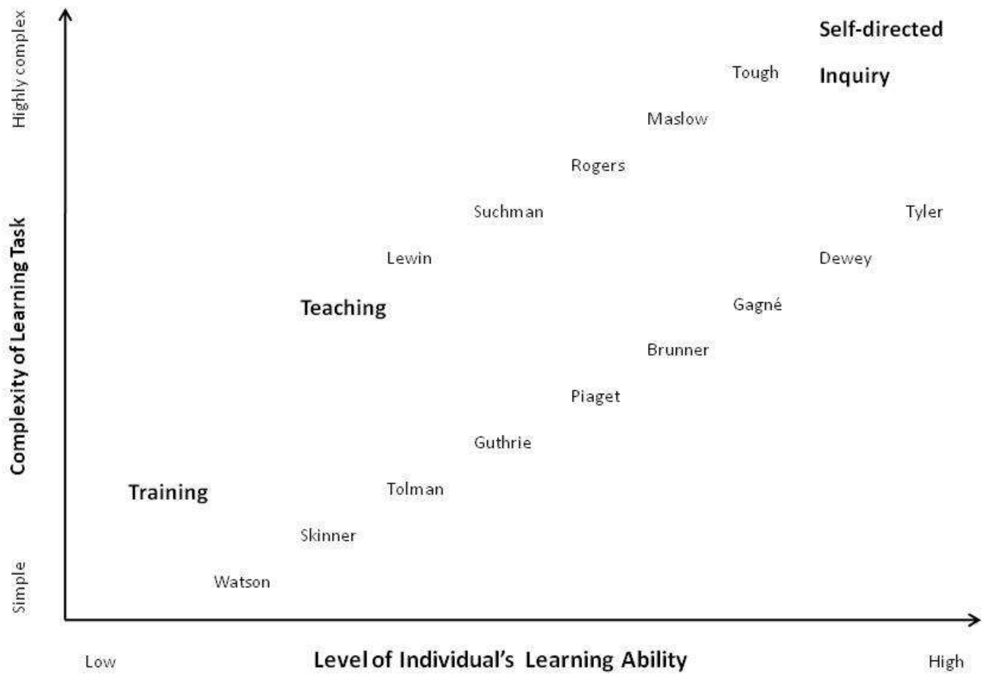

Figure 5: Relationship teaching models and learning situation [129]

The adaptive system which is the goal of this research aims at fairly complex learning tasks and consequently the learning theory and technology selection is mainly based on John Dewey's ideas and concepts related to them. Learning technologies described have been selected for their suitability in an adaptive online learning scenario.

3.2.1.1 John Dewey's Philosophy of Education

John Dewey's philosophy of education is most famous for introducing the concept of "learning by doing" and the emphasis on learning experiences. Dewey provides a conceptual design, based in educational philosophy. His theory encourages individuality, free activity, learning through experience, learning skills as needed, as well as opportunities developed in the present. His teaching strategy is guided by two main principles, continuity and interaction. Interaction needs to be continuous, building upon previous experiences and thus building up relevant and meaningful knowledge. This idea is grounded on the basic principle of habit, that every experience will change our perception of future experiences, because it changes the person and thus the person facing the following experiences. Dewey argues that the value of an experience is determined by the perception of the resulting relationships or other consequences.

Positive learning experiences encourage further learning and exploration, but again “everything depends upon the quality of experience” ([51] p.16). Quality of experience has two aspects according to Dewey, agreeableness and influence on later experiences. The influence of previous on succeeding experiences is called the *continuity of experience* or the *experiential continuum*. Agreeableness refers to the fit into the frame of reference of previous experiences ([51] p.44).

According to Dewey, knowledge is not accumulated for the theoretical case of application in the future, but it is accumulated by making it relevant to the learner and creating learning experiences with that knowledge.

Dewey’s theory can be summarized, stating that continuity and interaction determine experience. The learning experience from one situation equips the learner in new ways for coming learning situations and opportunities for interaction. Continuity and interaction provide a measure for experience. To fully benefit from a learning experience, the learning environment, the subjects as well as the individual conditions of the learner have to be in accordance. Teaching has to adapt the external environment and to the changing needs and capacities of the individual learners.

Adaptive hypermedia is characterized by a user model, describing information about the user, an adaptation model, describing the adaptation policies, enabling adaptation to changing user needs and a domain model that describes the learning domain in adaptive e-learning systems. More detailed information on adaptive hypermedia is presented in the following sections. Dewey’s ideas can be mapped to basic technologies and tools typical for adaptive hypermedia [5] (see Table 1).

Table 1: Concept and Technology Mapping

Dewey's Concept	**Supporting Technologies**	**Tools**
Learner	User model	n/a
Continuity	Adaptation module & user model	n/a
Avoid overindulgence	User model	n/a
Free activity	Adaptable presentation	Podcasts, blogs, wikis, multimedia sharing
Learning skills as needed	Adaptation module	n/a
Individual learner needs	Domain model	n/a
Develop opportunities in the present	n/a	Wikis, blogs, multimedia sharing

The learner is represented by the user model, which captures for example previous knowledge, learning goal and demographic information. The *continuity* of the experiences is provided for by the adaptation module, which uses information stored in the user model database and balances it with the information of the actual activity and progress of the learner. *Overindulgence*, *learning skills as needed* and *individual learner needs* is dealt with by the combination of user model information and adaptation module. *Free activity* and *develop opportunities in the present* is not always catered for in an adaptive systems. It can be done by providing opportunities to make decisions on the adaptivity as well as providing open learning opportunities rather than guided learning. Opportunities to actually create or develop something can be catered for by including web 2.0 technologies, such as wikis, blogs or options for multimedia sharing. This basic mapping shows how Dewey's theory can support improving QoE in an adaptive hypermedia system.

3.2.1.2 Adult Education

This research is primarily concerned with systems used for adult education. Knowles [129] developed an andragogical model for adult learners. He shares with Dewey the inclusion of informal, semi-structured learning. In contrast to pedagogy, which focuses on learning of children, it focuses on learning of adult learners. The model is based on several assumptions typical for learning situations of adult learners which differentiates them from younger learners and pedagogical approaches:

1. The need to know
2. The learner's self-concept
3. The role of the learners' experience
4. Readiness to learn
5. Orientation to learning

Adults learn, because they have identified that they have a need to know the course content. Supporting the adult learner therefore means showing them where or how to apply new detailed knowledge in real life. Adults not only vary in learning style, but more strongly in their goals and their previous experiences. Naturally adult learners will bring a bigger variety of individuals into the classroom than younger learners and this will affect the learning experience. Adults usually have a self-concept of being responsible for their actions, which can easily collide with a hierarchical pedagogical teacher-learner relationship.

The discussion about the need for an andragogical model is a fairly new one – unlike andragogy itself. Teachers of ancient times such as Confucius, Aristotle, Socrates and Cicero were all adult educators. Learning in that tradition is named *active inquiry learning* and it actively engages learners through techniques such as case methods, debate and Socratic dialog. The experience of the adult learner will be affected by the way the system recognizes the individual characteristics of the learner. Accounting for the learner as an adult by using appropriate language, tasks, and providing opportunities to adapt the system to their individual needs should support QoE of the learner.

3.2.1.3 Learning Styles

Learning styles and cognitive styles are two terms often mixed up and used as synonyms. Cognitive style describes how we process information in general. Learning styles describe the way we process information in a learning environment [22]. The role of learning styles has been discussed widely over the last 25 years and numerous learning styles models came out of these discussions. All learning styles models have in common that an initial assessment of learner characteristics leads to a categorization of the learners. Learning materials are then optimized to match the identified learning style category, aiming at supporting individual learning preferences.

Learning styles can be categorized into families of learning styles ([31], p.10), based on their key concepts and definitions that are shared within each group. However, despite all the research and the development of different models, it has not been established yet that this optimization actually improves the learning [175] [148].The following learning styles models have been selected previously for research and/or adoption in the education sector. The different models can be summarized in a taxonomy of learning styles models (see Table 2).

Table 2: Taxonomy of Learning Styles Models

Key Concepts / **Model**	Kinesthetic / sensory	Trial & error	Verbal / aural	Visual	Read/write	Reflective	Structure	Group work	Global
Riding [182]			●	●					
Witkin [225]							●	●	
Kolb [22]	●	●			●	●	●	●	
Felder [61]		●	●	●			●	●	●
Myers-Briggs [22]	●		●				●	●	●
VARK [65]	●		●	●	●				
Pask [22]		●					●		●
Dunn & Dunn [22]			●			●	●	●	
Gregorc [193]	●	●	●	●			●		
Paivio [171]			●	●					
	4	4	**7**	**5**	2	2	**7**	**5**	3

The taxonomy categorises the models along key concepts of the models. Two meta-categories become obvious; models are either focusing on the type of interaction with the learning materials (kinesthetic/sensory, trial & error, verbal/aural, visual, read/write, reflective) or else on organizational issues (structure, group work, global). Both meta-categories have clear emphasis on two concepts each. For the organizational issues structure and group work are emphasized; both issues can be dealt with during instructional design.

The verbal/aural and visual categories are emphasized by most models in relation to interaction with learning materials. Therefore these are taken as central categories for consideration of learner preferences, as described in multimedia learning theory.

3.2.1.4 Motivation in Multimedia e-Learning

Multimedia learning theory [150] is based on the dual coding theory [171], which states that human cognition processes knowledge in two sub-systems simultaneously. Each of the two sub-systems processes either nonverbal (i.e. images, sounds) or verbal information (i.e., spoken or written words). Important elements of this concept are that humans process visual and verbal information in different channels, that each channel can only carry a limited amount of information at any given time and that learning requires involvement in active cognitive processes such as selecting, organizing, integrating [152]. Mayer’s [151] model for the cognitive theory of multimedia learning outlines the main processes in multimedia learning (see Figure 6).

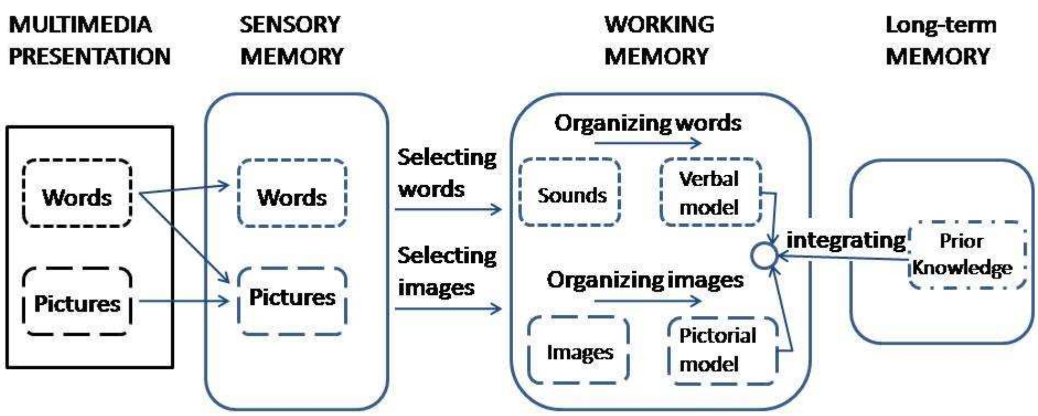

Figure 6: Cognitive Theory of Multimedia Learning [151]

It shows how the components of words and pictures in media are split up between two sensory channels. The mind makes sense of sounds and images by organizing them into verbal and pictorial models, influenced by prior knowledge from the long term memory. This also shows that using the same channel twice, e.g. by providing on screen the transcript of an audio explanation, would cause redundancy and overload the verbal channel.

Research on motivational techniques for e-learning shows the positive motivational impact [211] of alternating delivery and format into the media mix strategy. The change of media format adds an element of variability, which has been identified as another motivational technique [107]. A media mix that varies the media format, presenting one media type at a time, prevents overwhelming the learner and leaves room for visual rests [29]. In courses with high equivocality it supports learning satisfaction [206].

The combination of these two aspects indicates that a mix of different media, preferably media that caters for information input on both channels (illustrated text with video rather than audio) supports learning.

3.2.2 Learning Methods - From Guided Instruction to Problem Based Learning

Although there is considerable lack of clarity whether students learn better with guided or inquiry-based instruction, both theories have been implemented in adaptive systems. Clark [29] found that learners with less learning ability tend to choose a less guided approach although they learn less that way. Higher aptitude students choosing the highly guided approach on the other hand tend to learn less with more guidance. Less guided approaches have been implemented in adaptive systems [18] [154] as well as very structured teaching approaches. The effectiveness of problem-based learning has been widely discussed with almost equal numbers of studies in agreement or disagreement with the method [81]. All three methods are related to Dewey's initial ideas and in particular the focus on experiences – which makes them suitable to have a closer look.

One of the main differences, despite the common base in Dewey's ideas, is the role of the teacher or tutor [186]. In guided instruction the teacher has a very active role, and guides the learner almost step-by-step in all his or her learning activities. In inquiry-based learning the tutor facilitates learning and provides information, activities become more student-centred. Problem-based learning requires tutors to facilitate the process of higher-order thinking, but not to supply information. Now the student clearly holds the active role whereas the tutor supports this (see Figure 7).

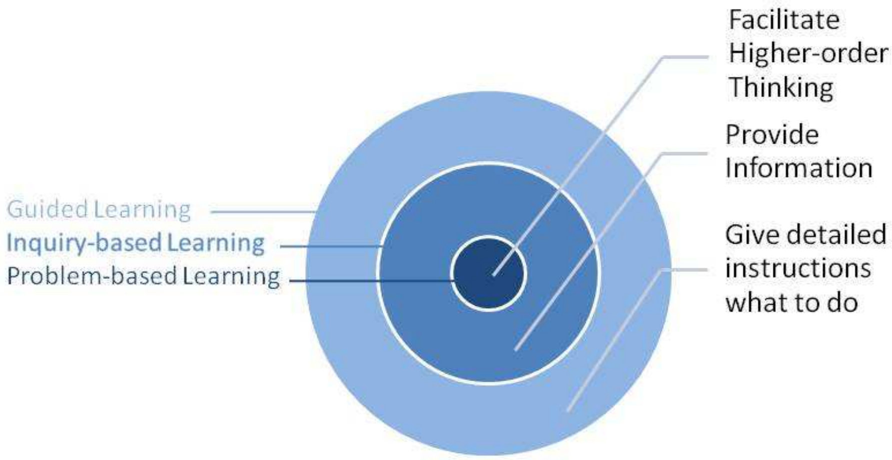

Figure 7: Role of the Tutor/Facilitator in Different Learning Methods [8]

Guided learning is what Dewey describes as traditional learning. It summarizes a teacher-centred approach to learning and is not considered state of the art, although can be found commonly as state of the practice. Direct instruction or guided learning concepts are explained fully as well as the procedures the student has to follow and the learning strategy.

Inquiry-based learning describes learning with more freedom, but also responsibility of the learner. The tutor or teacher still provides information, but not all procedures are explicitly presented.

Problem-based learning (PBL) has been described as the method where students encounter a problem, and then they do a systematic inquiry which is followed by a reflection process [8]. PBL has three aims: 1) provide an opportunity to acquire factual knowledge in a useful and for the learner later on applicable context, 2) learn principles and concepts in a way that facilitate transfer to other problems and 3) gain experience with similar patterns to answer future questions.

Guided instruction and inquiry-based learning will be used in the prototype to test the QoE adaptation policies, leaving the decision on the learning method to the learner. Access to both types of learning method are provided by a book-like navigation for the guided instruction and a typical website navigation allowing access to all learning materials and therefore support inquiry-based learning.

3.2.3 Learning theory for online learners

One of the first obstacles in e-learning is the fact that we never or rarely meet the learners face-to-face. To compensate for this deficiency, different concepts and theories have been developed, learning styles being one of the more diverse and popular ones [100] [23]. There is as much research in favour of learning styles [67] as there is, showing that learning styles do not have an impact on the learning results [148] [175]. Research shows the value of adaptivity based on cognitive style [213] [83], whereas other research shows that learning is best when it combines a mix of verbal and visual information [148] [79], ignoring preferences indicated by learning style. It has been shown that results do not improve when adapting to materials the learners have marked as preferred [124] [80]. Some research could confirm that matched materials lead to better learning results [67], but only for male participants of the study.

Research shows that students learn better when instructional material does not force them to split their attention between multiple sources of information and if verbal information complementing visual information is presented auditory rather than as on-screen text [160]. Learning improves also if animation and narration are combined in one source and therefore presented simultaneously.

Multimodality of visual and verbal communication has proven to be successful for different learner groups such as undergraduate and postgraduate e-learners as well as educators in higher education [224]. Research results indicate that all three groups prefer more visual communication than is usually available in e-learning environments. This indicates that visual material like videos should be included more in e-learning scenarios aiming at good quality of experience for the learner. It does not imply though to get rid of text-based e-learning altogether.

Online learners apparently choose learning materials which match their learning styles, but that does not enhance their learning [148]. For my research this means that completely unguided, open learning might not support my goal of enhancing the quality of experience, which combines satisfactory learning results and learning that captures the learner’s attention.

3.2.4 Summary of Learning Technologies

The individual learner can be described by the learning style, but a synthesis of the learning styles shows that a lot of the models contain two characteristics, verbal and visual communication. Theory points out that a mix of media can provide sufficiently individualized learning. This can be considered the core of multimedia learning theory, in particular that a mix of different media supports learning and enhances motivation of the learners. Learners perform best when both channels, verbal and visual, complement each other.

Dewey's philosophy of education and its emphasis of individuality, free activity, learning through experience, learning skills as needed, as well as opportunities developed in the present is the basis for Knowles andragogy, education for adult learners. Dewey is also the base for learning methods like problem-based as well as inquiry learning. Guided learning on the other hand comes closer to what Dewey outlines as the traditional learning strategy, characterized by a set body of knowledge, standards and rules developed in the past to determine moral education in conformity with these standards and a hierarchical school organization and very formal relationships between the students as well as the students and their teachers.

3.3 Adaptive Hypermedia

Adaptive hypermedia systems "tailor content presentation and navigation support to individual users by taking into account a model of user's goals, interests, and preferences" [25]. Adaptive Hypermedia is not a new area; a brief history of AH outlines the background of current research, some of the first hypermedia systems and current trends. Most of these systems have a very similar architecture, which is described next. The focus of this research is Quality of Experience in adaptive and for reasons of comparison, non-adaptive multimedia e-learning systems. A selection of these systems are described and compared in relation to their adaptive potential.

3.3.1 A Brief History of AH

Adaptive Hypermedia System (AHS) is a new generation of hypermedia systems and research in this area started in the 1980s (see Figure 8), bringing together the two areas hypermedia and user modelling. Hypermedia is an extension to the term hypertext in which graphics, audio, text and hyperlinks create a generally non-linear medium of information. Bringing the user model to hypermedia, the non-linear medium of information is changing according to the user preferences for a device, their goals, knowledge, etc [13] [14]. Existing adaptation models often have close connections to the Dexter model, one of the first models or they introduce new technologies to this basic model, such as XML (XAHM) or multi agents (MODA).

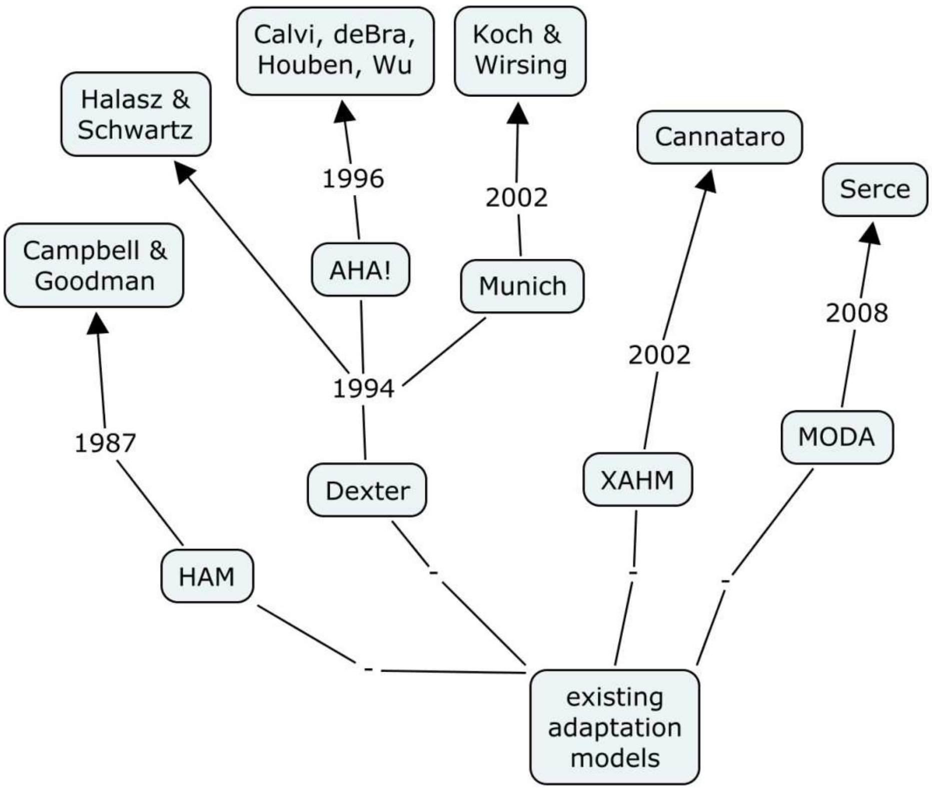

Figure 8: An incomplete family tree of Adaptive Hypermedia

HAM, or *hypertext abstract machine* was one of the first systems and it was developed around 1987 by Campbell and Goodman [21]. It is a transaction-based server for a hypertext storage system and consists of contexts, nodes, links, and attributes that form a hypertext graph.

The **Dexter reference model** was developed by Halasz and Schwartz [89] in the early 1990s. It divides a hypertext in three layers, the run-time layer, the storage layer and the within-component layer, with a focus on the storage layer. The storage layer models the node and network structure of the hypertext. Within-component layer describes exactly that, the content and the structure within the components of the network. The run-time layer finally provides tools for the user to access view and manipulate the network structure.

AHA! was inspired by the Dexter model just like the Munich reference model. *AHA!*, the adaptive hypermedia architecture was developed in the Netherlands by a research group around Paul deBra [42]. In 1996 an online course was enhanced with adaptive content and linking. *AHA!* version 3.0 has been released in 2007. The two main components of the system are the rule engine, which generates updates of the user model out of the user's actions and the adaptive resource selection, which provides the adaptation of the content and the navigation. There are a number of side projects, e.g. LAOS, the authoring module [40]. Learning styles have been implemented [201] for AHA!. AHA! has been used in a lot of research in adaptive hypermedia, because it is freely available, although not well documented.

The **Munich Reference Model** [130] is also an advancement of the Dexter reference model, similar to the adaptive hypermedia authoring model (AHAM), a model developed in the vicinity of *AHA!*. The novelty in the Munich reference model, is that the object-oriented specification is written in UML (Unified Modeling Language), combining a visual representation and the formal specification in OCL (Object Constraint Language). It adds user modelling aspects and rule-based adaptation mechanisms to the model.

XAHM is an XML-based adaptive hypermedia model and is a representative of a number of similar reference models e.g. [4], taking existing models and enhancing them by using XML for the description of metadata about basic information fragments and to adapt "neutral" pages. XAHM is based on three different "adaptivity dimensions": user's behaviour such as preferences and browsing activity; technology such as network and user's terminal; and parameters for the external environment such as time, location, language, socio-political issues, etc..

MODA [192] is a multi-agent module to provide micro-level adaptiveness in learning management systems and represents the teaming up of two types of systems, adaptive and learning management systems. There are currently a number of projects aiming at either making adaptive systems more user friendly or making learning management systems adaptive, e.g. ALS (http://www.als-project.org/), Grapple (http://www.grapple-project.org/).

3.3.2 Basic Architecture and Features of Adaptive Hypermedia

AHS refers to all hypertext and hypermedia systems which collect information on the user, stored in the user model and then adapt system features accordingly [14]. The architecture of an AHS for e-learning, an adaptive learning system (ALS) not only consists of a user model, but also includes a domain model and an adaptation model (see Figure 9).

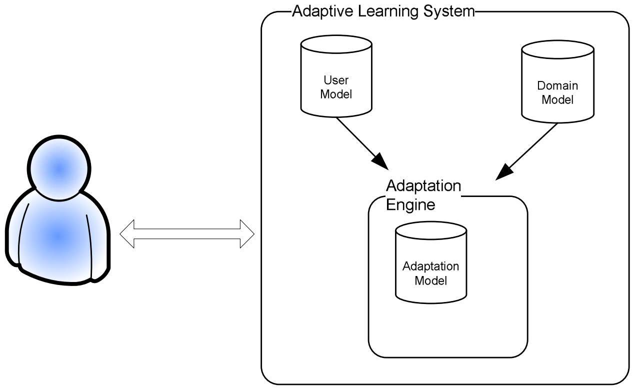

Figure 9: Basic Architecture ALS

The user model represents characteristics of the user, their goals, their knowledge, and their device preferences. The domain model represents the concepts of the subject domain and it describes these concept structures as concept maps, semantic networks or concept graphs. The adaptation model connects the two previously outlined models and any models relevant for the adaptation to the user's needs, using adaptation rules. It thus enables individualized selection matching the preferences of the user.

Adaptive hypermedia systems are used in domains like e-learning, e-commerce, e-government. The most popular adaptive hypermedia systems are web–based systems. In recent years, e-learning is used in a wide variety of contexts, from companies to secondary schools and universities.

In contrast to traditional e-learning and face to face education systems, which deliver the content of the course in the same way for every student, adaptive educational hypermedia systems adapt to the learner. The course can be adapted to the learner's goals, abilities, needs, interests, and knowledge, as defined by the user model.

Depending on the user model the adaptive hypermedia system will guide the learner what to read and learn and will change the content, navigation or other adaptive features of the system accordingly. The methods and techniques mainly applied are adaptive navigation support and adaptive presentation.

In order to present the content to the learner the link-level adaptation adapts the structure of the navigation path to the user model of every learner. The navigation support changes the link structure, the link destination and how these links are presented.

In [14] we find a classification of the Adaptive Navigation Support (see Figure 10).

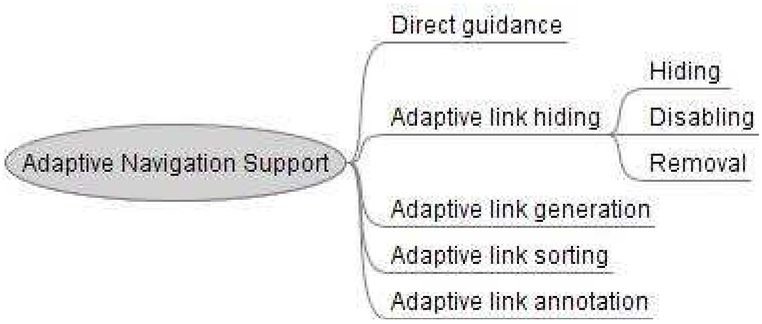

Figure 10 Adaptive Navigation Support

With direct guidance the student is lead to the following step by a "next" or "continue" button. If there are many links provided, adaptive link hiding is an option, which disables or removes irrelevant links. Link anchors can also be represented in different ways (wording, style and appearance) depending on their importance by link annotation. If a list of links is presented, these can be sorted by their importance. Figure 11 shows an example of adaptive navigation from Knowledge Sea [15].

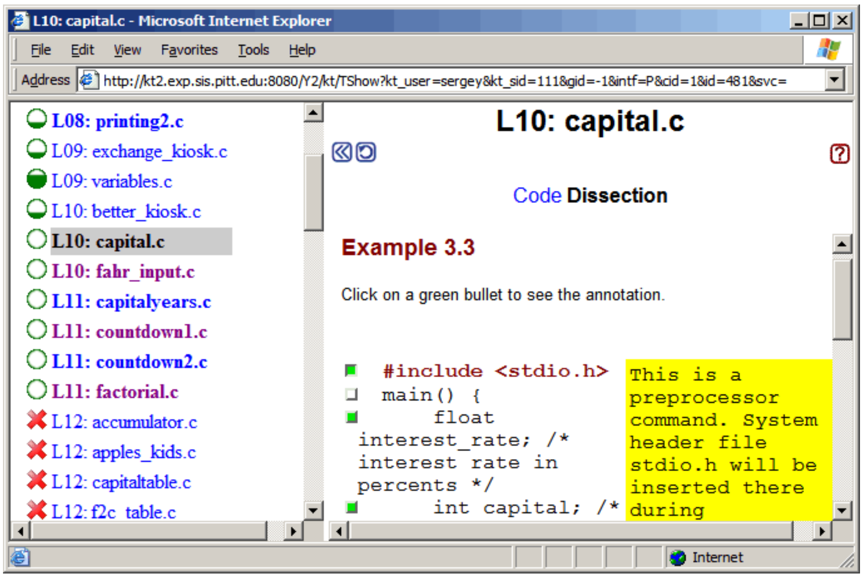

Figure 11: Screenshot Navigation Knowledge Sea

Adaptive content presentation adapts the content according to the goals, knowledge background, knowledge level, learning styles and other information from the learner or user model. For example a beginner may require some explanation for a technical term or need a simple version of a course, while a more advanced learner might prefer a more complex version. Depending on their preferences some learners might prefer text, while others learn more easily with audio material or some other media format.

Figure 12 shows Brusilovsky's adaptive presentation taxonomy and the 3 categories of adaptive presentation adaptive multimedia presentation, adaptation of modality and natural language adaptation.

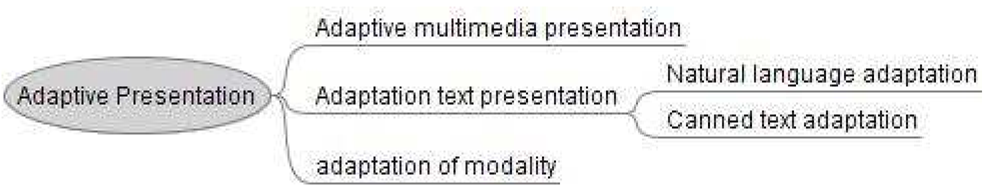

Figure 12: Adaptive Content Presentation

Adaptive multimedia presentation is the manipulation of multimedia content like video or image quality and size. Adaptation of modality is the selection of the type of media and the most used text presentation. Natural language adaptation is still hard to implement; so-called canned text adaptation relies on methods like inserting and removing fragments of (conditional) text, altering fragments, stretching text, sorting fragments and dimming fragments.

3.3.3 Adaptive versus Non-adaptive Learning Systems

The variety of e-learning systems can be divided under many paradigms. A recent study [95] divides the systems into popular and adaptive systems. The following paragraphs highlight a few of the systems investigated. Relevant adaptive e-learning applications using the technologies outlined previously are mainly used in research, while the popular Learning Management Systems (LMS), and usually cannot provide adaptability.

All non-adaptive systems presented are open-source software, because this enables modification, which is more suitable for research. Most of them are used in universities as well as for training purposes. The brief introduction lists the main features and provides a screenshot. The screenshots are not meant to enable detailed analysis of the GUI. They should rather give an overall impression and enable the reader to see the commonalities of the non-adaptive, but popular systems and their difference to the less designed adaptive systems following afterwards.

Moodle [53] is a learning management system (LMS) and the name was originally an acronym for Modular Object-Oriented Dynamic Learning Environment. Moodle is guided by social constructionist pedagogy, and therefore works well for implementing teaching that follows Dewey's ideas.

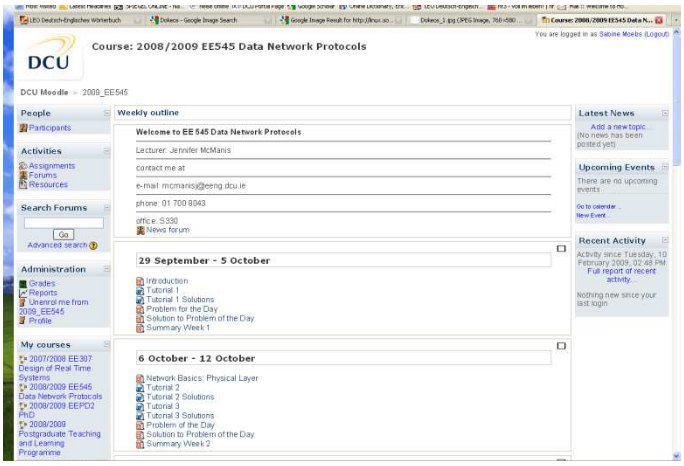

Figure 13: Screenshot Moodle

Dokeos [52] is a course management system (CMS) and evolved from the LMS “Claroline”. It enables SCORM import, edit and export. SCORM stands for Sharable Content Object Reference Model and it is a collection of standards and specifications for e-learning [72]. Social interaction is supported by tools such as forums, chats, groups and web conferencing. Extensive documentation for users and developers alike is provided in the Dokeos Wiki.

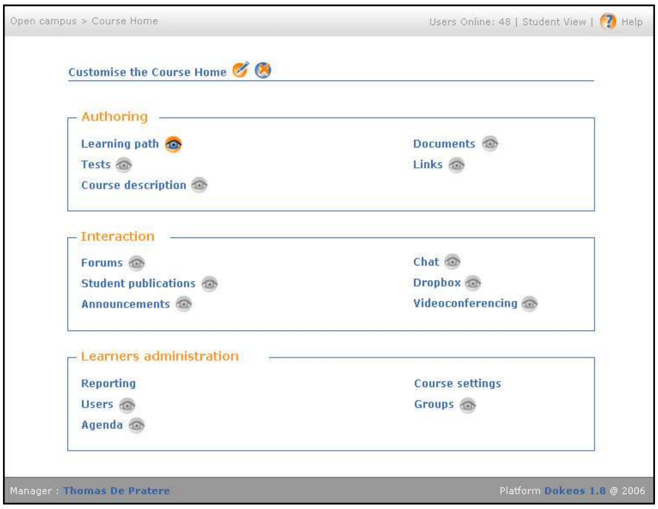

Figure 14: Screenshot Dokeos

Claroline [30] is web based CMS and it is under The GNU General Public License. Documentation is available in a wiki in several languages. A forum provides the opportunity to exchange experiences and ask questions on all aspects of a CMS.

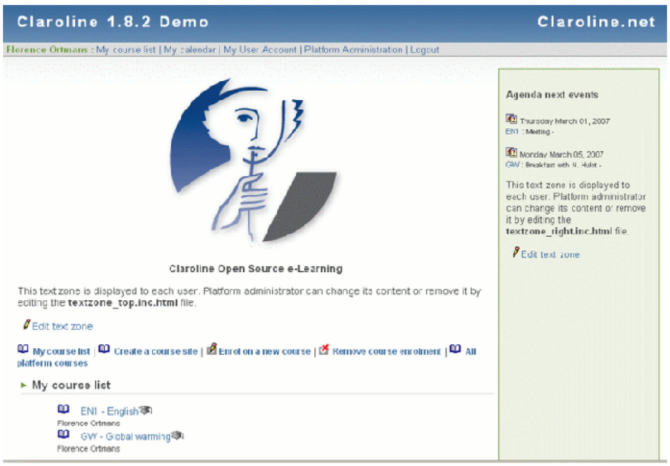

Figure 15: Screenshot Claroline

Sakai [185] is a collaboration and learning environment (CLE). It also provides SCORM compatibility. It specifies the sequence in which a learner will experience the learning objects, which restricts the learner's choice which path to take through the learning material.

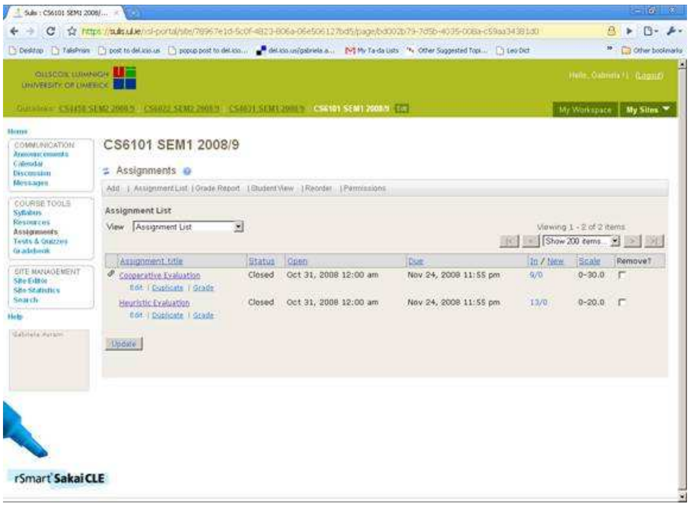

Figure 16: Screenshot Sakai

Ilias [112] is a web based LMS. It provides a repository with role based access control, learning content in different formats (XML, SCORM, AICC) and standards compliance with LOM, SCORM 1.2, SCORM 2004, IMS-QTI, AICC. Web 2.0 features supported are chat, forums, RSS, Google maps support and podcasting.

Figure 17: Screenshot OLAT

The following paragraphs outline the two most used adaptive e-learning platforms, both are open source software. The first system presented, InterBook, is only available as open-source software for Macintosh. The systems are mainly used for research purposes. The brief introduction lists the main features, additional information and a screenshot.

InterBook [113] is a tool for authoring and delivering adaptive electronic textbooks online. It applies principles of adaptive hypertext and hypermedia. Its individual learner model for every user enables adaptive navigation support and adaptive help. Its adaptivity has been improved by combining it with AHA! (see Figure 18), the system introduced next. The new version is called InterBook@AHA! and it combines the easy content development from RTF files and the presentation interface from InterBook with the adaptation engine from AHA!. Adaptive features are link annotation by colour and icons and conditional fragments hiding non-suitable content. It furthermore provides help through generated "suggested readings".

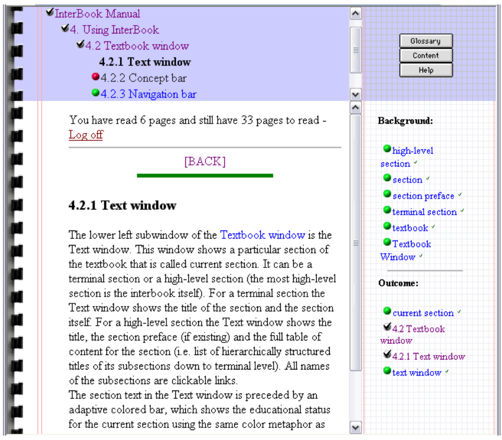

Figure 18: Screenshot InterBook

AHA! [42] (see Figure 19) is an open-source project and it provides adaptive presentation support, adaptive navigation support and link annotation. The adaptive presentation includes adaptive multimedia presentation, adaptive text presentation and adaptation on modality. The adaptive text presentation initially was the most unique feature of the system together with inserting and removing fragments, altering fragments, stretch text and dimming fragments. *AHA!* has a web-based adaptive engine and is built on Java Servlet technology. It works best with Apache/Tomcat, but it also runs with other servers. The authoring is implemented through Java Applets. AHA! consists of a general-purpose user-model combined with adaptation rules. In version 3.0 in particular *AHA!* uses XML and for database support it is using mySQL.

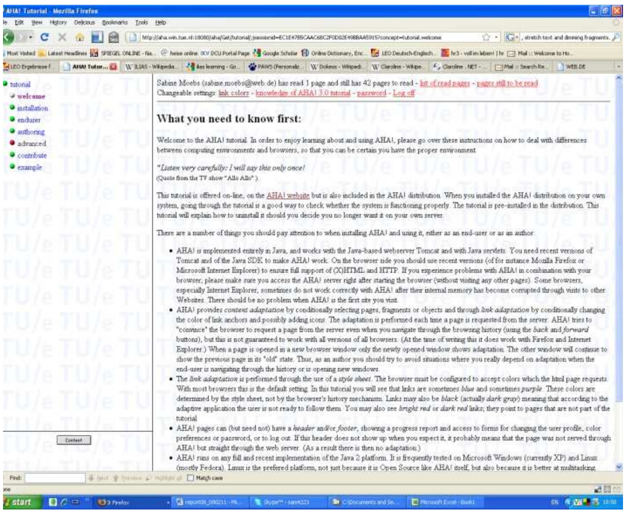

Figure 19: Screenshot AHA!

Most adaptive systems are used in research to test and implement new adaptive techniques, but they lack a rich interface for the user (student).

Adaptive e-learning systems provide adaptive guiding, link annotation, link hiding and adaptive presentation support. But they provide fewer features for collaboration (chat, audio and video conferencing). They do neither invite human interaction nor strengthen individuals' social networks [95].

CMS or LMS typically do not provide adaptive features, but they have a rich interface. They usually also provide communication tools and tools for collaborative e-learning. A comparison of both types of systems with selected features highlights this and it is shown in Table 3.

Table 3: Selected Features of e-Learning Systems [95]

System / Feature	Dokeos	Moodle	Sakai	AHA!	InterBook
Adaptivity					
Link Annotation				X	X
Link Hiding				X	X
Adaptive Presentation				X	X
Learning Management					
User Group Support	X	X	X		X
Stored Learner Model				X	X

3.3.4 Standards in e-Learning

E-learning courses are often developed in the context of large company projects. Standards were developed to enable reusability, interoperability and to support quality management. Prominent standards are IMS, ADL SCORM and AICC specifications [173]. SCORM enables content sequencing, while IMS LD describes learning scenarios [72]. AICC specifications were one of the first standards available [197] and supports launches of a course and receiving tracking and scoring information. The diversity of standards has triggered mainly two reactions in the context of adaptive hypermedia. The first is to argue that most of the standards do not support adaptive e-learning sufficiently [173]. Secondly many of the existing standards do not have sufficient tool support yet and it can be argued that this should be the main goal before developing more standards without sufficient tools, technologies and methodologies support [54] [158]. Both arguments are strengthened when considering SCORM-compliance for multimedia e-learning, since most standards evolved from concepts including a lot less different media.

3.3.5 Authoring Adaptive Hypermedia

The authoring process for adaptive hypermedia enables the provision of courses that can be adapted to various conditions, which can be defined in the adaptive system. This authoring process has to consider the needs of the author, who increasingly is a non-technically trained person [37]. The necessity to define adaptation strategies led to the development of a specialized language [39]. This was followed by research to make strategies written in this adaptation language reusable [103] and finally merging strategies for authoring adaptive hypermedia [190]. While these strategies enable authoring of adaptive courses, the implementation is often not suited for non-technical authors. Initial authoring tools aimed to enable the authors to feed course content into an adaptive system without having to interact directly with the often complex adaptive systems [38]. Current authoring tools aim for a shallow learning curve from the authors [71] and enabling transformation of existing linear into adaptive modules [69], also providing specialized support for the authoring strategies [70].

3.3.6 Summary of Adaptive Hypermedia

The majority of current adaptive systems are derived from the Dexter model, which was developed almost 20 years ago. The main feature that is still maintained is the three layer structure, consisting of the run-time layer, the storage layer and the within-component layer. The basic architecture of adaptive systems consists of the user model, the domain model and an adaptation model. This enables the adaptation of either content or navigation, adapting to a variety of parameters. In e-learning there are a number of open source hypermedia systems available. They are either called learning management systems such as Moodle and Ilias or course management systems, Dokeos and Claroline and finally Sakai, a so-called collaboration and learning environment. All of them are virtual learning environments (VLE). In comparison to these systems AHA! and InterBook, both adaptive platforms for e-learning, provide adaptivity that enables individualized system features, however these two adaptive systems lack the possibilities for collaboration and are less user-friendly and due to less GUI design effort.

3.4 Quality of Service

The following section highlights Quality of Service (QoS) concepts and parameters relevant for applications commonly used in multimedia e-learning.

In the context of this research QoS attributes and parameters taken into consideration are loss, delay, jitter and bandwidth. Applications considered are web access, audio and video.

3.4.1 QoS Target Values

The International Telecommunication Union (ITU), a United Nations agency, provides a number of target performance parameters [119]. The parameters are recommendations for end-user multimedia QoS categories (see Table 4).

Table 4: Target Performance Parameters [119]

Medium	Service application	typical amount of data / data rates	one-way delay	delay variation (jitter)	information loss (2)
audio	high quality streaming audio	1-2 Mbit/s 16kB/s to 128 kB/s(3)	timely delay ~10 sec	<<1 msec	< 1% PLR
video	broadcast	16kB/s to 384 kB/s	timely delay ~10 sec	no value	< 1% PLR
data	webbrowsing HTML	~10 kB	Preferred <2 sec/page Acceptable <4 sec/page responsive delay ~2 sec	n/a	zero
data	bulk data transfer/retrieval	10kB to 10 MB	Preferred <15 sec/page Acceptable <60 sec/page timely delay ~10 sec	n/a	zero
data	still image	<100 kB	Preferred <15 sec/page Acceptable <60 sec/page timely delay ~10 sec	n/a	zero

The recommendations provide a first indication which parameters are of special significance for the different media and applications.

The tolerance towards QoS parameters depends on the application (see Table 5). In case of multimedia e-learning web access, audio and video on demand applications are taken into consideration.

Table 5: Stringency of QoS requirements [210]

	Reliability	Delay	Jitter	Bandwidth
Web access	High	Medium	Low	Medium
Audio on demand	Low	Low	High	Medium
Video on demand	Low	Low	High	High

Web access can tolerate jitter, but requires medium bandwidth and only some delay, while reliability has to be good. Audio and video on demand have the strictest QoS requirements. They require medium to good bandwidth and cannot tolerate jitter very well, reliability and delay are tolerated though.

From the different approaches to QoS in adaptive multimedia it becomes obvious that bandwidth is the most important parameter, which also has an effect on delay, jitter and loss.

Table 6 introduces QoS classes according to ITU recommendations [119], which can be used for reference. IPTD denotes IP packet transfer delay, IPDV represents IP packet delay variation, IPLR stands for IP packet loss ratio and IPER denotes IP packet error ratio.

Table 6: ITU-T QoS classes [59]

Network parameters	**Class 0**	**Class 1**	**Class 2**	**Class 3**	**Class 4**	**Class 5**
IPTD	100 ms	400 ms	100 ms	400 ms	1 s	undefined
IPDV	50 ms	50 ms	undefined	undefined	undefined	undefined
IPLR	0.001	0.001	0.001	0.001	0.001	undefined
IPER	0.0001	0.0001	0.0001	0.0001	0.0001	undefined

These QoS classes can be used in a QoS referencing table [196], which compares QoS metrics with corresponding classes. A QoS to QoE mapping based on the reference table shows that QoE requirements vary for different users and QoE can be improved relative to the individual, which also means that a fixed QoE-QoS mapping is not optimal.

3.4.2 QoS and User Perception in Adaptive Multimedia

Adaptive multimedia has to be distinguished from adaptive hypermedia. It is the area on adapting streaming media. User perception in adaptive multimedia can be approached from a number of different angles. Cranley [36] adapts encoding quality to different network conditions, aiming at a maximization of user-perceived quality. It is possible to degrade the quality, as long as the video stream is uncorrupted. The human vision system (HVS) will adapt to quality changes after a few seconds, therefore continuous quality changes soon become annoying.

Quality of Perception (QoP) is a concept which has been developed to enhance the previously outlined concept of QoS. Ghinea [76] describes it as the ability of the user to synthesize and analyze informational content. Initially QoP has been researched as a video specific concept. QoP is mapped to network parameters.

QoP of video, audio and text are mapped to QoS parameters bit error rate, segment loss, segment order, delay and jitter (see Table 7). Although one might expect that QoP for videos is most affected by frame loss, it is actually most affected by change in segment order, while audio requires that no segments are lost.

Table 7: Conversion matrix linking QoP to QoS [77]

QoP to QoS MAPPING		**QoP**		
		Video	**Audio**	**Text**
QoS	Bit error rate	Low	Low	Low
	Segment loss	Low	High	High
	Segment order	High	Medium	Medium
	Delay	Medium	Medium	Low
	Jitter	Medium	Low	Medium

Ghinea [78] states that user motivation to view a presentation has a stronger impact on the reported QoP than technical perspective. The QoP concept evolved further when looking at user perception in distributed multimedia quality, expanding a quality definition by Wikstrand [86]. The new, refined model differentiates between two perspectives, technical and user perspective, and considers three levels, network, media and content levels. Parameters defining the network level are delay, jitter, bandwidth and loss. The media level is characterized by frame rate, bit rate, screen resolution, colour depth and compression technique. And finally the content level is described by the level of enjoyment and the ability to perform a defined task. In more recent research [79] the model has been applied to an educational context and has been combined with the cognitive style concept of field dependence/independence. The results do not show any impact of QoS or cognitive styles on the QoP of the users. The results allow for the interpretation that in bandwidth constrained environments play back at maximum quality and consideration of cognitive styles for the personalization of multimedia systems is neither necessary nor helpful.

Another adaptation scheme for streaming video, the so-called Quality-Oriented Adaptation Scheme (QOAS), also considers user-perceived quality (QoP) in combination with network performance parameters [76].

QOAS adapts the video according to a five-state model, ranging from highest quality over above medium, below medium and medium quality to lowest quality. To evaluate the impact of QoS on QoP in an educational context [156] content type can be analyzed and videos then compressed accordingly. Four categories are differentiated, a full view of the classroom, a close-up of the teacher, slides and a typical shot in a question and answer session. Depending on the content and the respective compression, bandwidth demands vary, thus targeting bandwidth bottleneck situation which are the main constraint besides packet loss.

A further approach to adaptation for internet video streams considers receiver buffering, which adapts the video quality through variations of the available bandwidth [172]. The main aspect here is to favour smooth video of lower, but still acceptable quality, to jerky video at highest quality. The smooth video is enabled through an adaptation of receiver-buffered bandwidth variation. This requires feedback on bandwidth and round-trip-time (RTT) sent from the receiver.

Ghinea presents a QoS-QoP mapping [77] which is very similar to basic concepts of computer networks. His mapping points out that video are most affected by disruption of the segment order; audio and text are most affected by segment loss. From this he interprets that the information transfer ability of the media is depending on the respective network parameters. Adaptation therefore needs to consider the type of media when evaluating and adapting to network conditions. Ghinea found that media quality can be reduced significantly without users noticing [80], irrespective the cognitive style of the learner and without an effect of underlying QoS parameters on the perceived quality.

Verscheure [216] recommends considering coding bit rate and packet loss jointly to predict the video quality for high-resolution videos transmitted over lossy networks. The impact of packet loss depends on the compression algorithm and the available bandwidth; the higher the bandwidth the higher the encoding quality and the lower the packet loss rate (PLR). This reaches an optimum after which the quality drops again even if more bandwidth is available. This effect enables reaching a good, but very instable quality level. The optimal average bit rate is influenced by the video scene type, but is fairly independent of PLR. The optimal average bit rate can therefore be extended through mechanisms like adaptive quantization or forward-error-correction (FEC)-based protection. Adaptive quantization varies the step size for efficient compression based on changes of the input signal.

3.4.3 QoS Metrics

QoS metrics describe delivery characteristics and are often metrics for image and video services and can be classified as subjective methods, objective methods and reference-based methods [57].

Subjective methods require a human being involved in the evaluation of the quality. ITU [120] has specified how to subjectively measure quality in a controlled test environment. Quality measurement either uses one medium, as in single stimulus continuous evaluation (SSCQE) or participants are shown two versions of the medium in different quality, in double stimulus continuous quality scale (DSCQS). Both methods pool the voting of the participants in a mean-opinion-score (MOS), a widely used measurement for video quality. MOS has two main disadvantages though: 1) it is very cumbersome and cannot be implemented in real-time and 2) it cannot be implemented automatically. This makes it unsuitable for any real-time evaluation [222].

Real-time evaluation applies objective measures and can be differentiated in psychophysical and engineering methods. Psychophysical methods are based on aspects of the human visual system (HVS). On the one hand these models and the metrics based on them get very complex and computationally expensive, because they are modelled on the human visual system. But then that is their benefit; they are very close to human perception. Some examples for this method are picture quality prediction based on visual models [144], visual discrimination models [142] or multidimensional modelling of image quality [147]. Engineering methods are mainly based on image analysis and feature extraction, sometimes in combination with some aspects of HVS. These can be simple numerical measures [58], based on measuring simple features like normalized mean square error

(NMSE) and peak-signal-to-noise-ratio (PSNR) or more complex extraction and analysis algorithms.

Reference-based methods summarize quality metrics depending on their relationship to reference information. There are three main types: no-reference, reduced-reference and full-reference methods. No-reference methods have no information of the original medium available. A recent survey [57] comes to the conclusion that reduced-reference quality assessment methods are a good compromise between full-reference and no-reference methods. They provide a measure of quality degradation rather than an absolute quality measure, but on the downside they have a big overhead.

All the QoS metrics are looking at the receiver side of the transmission, which in our scenario could be too late for the adaptation decision. PSNR as a commonly used method is more detailed than human perception. This difference in detail granularity makes PSNR unsuitable for the assessment in user testing.

3.4.4 Summary of Quality of Service

The network performance parameters loss, delay and bandwidth are commonly used as input for adaptation decisions among most adaptation schemes. These parameters have to be evaluated differently depending on the media used. The ITU QoS classes can be seen as basic reference values for adaptation decisions based on network performance parameters. This requires real-time estimation of said network parameters. More complex measures of QoS such as PSNR as one of the commonly used full-reference QoS metrics cannot be considered for adaptation as they require big overhead and look at QoS after the adaptation decision. It is possible that subjective testing could be used to outline adaptation policies which would then be complemented later with objective parameters.

3.5 Flow

Flow affects navigation patterns as well as the frequency of repeat visits on commercial websites [195]. The success of visits depends on the level of involvement and flow and has been defined as "the state in which people are so involved in an activity that nothing else seems to matter" [41]. We will look at the flow experience in computer-mediated environments. If flow has such a strong impact on internet users, it most likely has an influence on e-learning. Previous research on QoE in e-learning [97] has not taken this concept into consideration. The summary looks at the benefits a remote learner from the initial scenario can get out of the different aspects of flow.

3.5.1 The Concept of Flow Experience

The concept of flow was first introduced by Csikszentmihalyi [41] and it represents the optimal experience or complete absorption with an activity. It is characterized by 8 dimensions, which can be divided into three stages: antecedents, experiences and effects (see Figure 20).

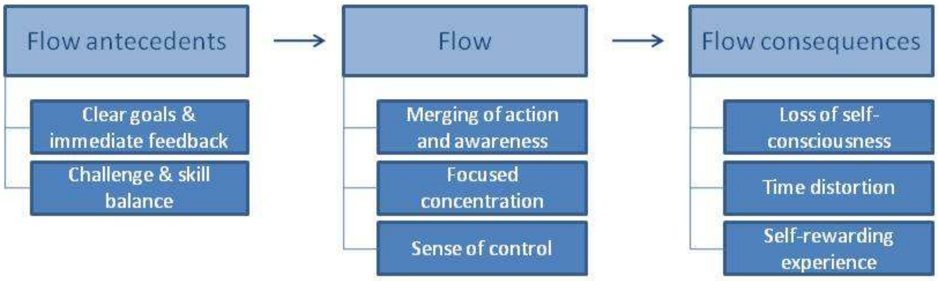

Figure 20: 8 Flow Dimensions (Csikszentmihalyi) [41]

The dimensions allocated to the antecedent stage are a clear set of goals, immediate feedback and equilibrium between challenges and skills. The experience stage is characterized by the merging of action and awareness, focused concentration and a sense of potential control. The final effects stage is characterized by a loss of self-consciousness, time distortion and a self-rewarding experience.

Flow as the “optimal experience” is based on the flow theory’s assumption that flow is a channel between anxiety and boredom, determined by the skill and challenge ratio [41], which formed the original model of flow (see Figure 21).

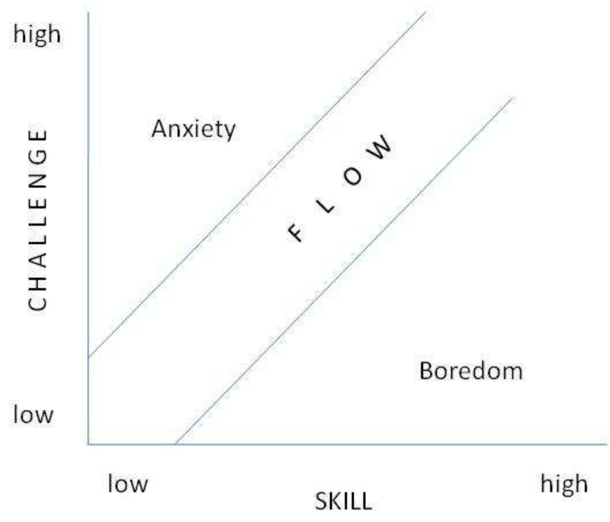

Figure 21: Original Model of Flow [41]

This model was developed further to the four-channel model of flow, which distinguishes states of anxiety, apathy, boredom and flow (see Figure 22). Just like the original model it is based on the challenge and skill balance. Anxiety being the state where the skill is considerable lower than the challenge, apathy where low challenge meets low skill, boredom the situation of high skill and low challenge and flow when high skill meets high challenge.

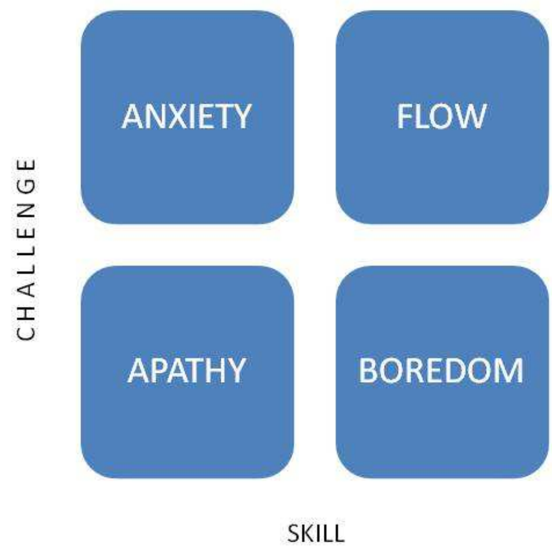

Figure 22: Four-channel model of flow [108]

Research shows that a number of typical online activities are related to flow. Information searching or surfing and following hyperlinks, reading, writing, online social interaction via chat or VoIP, actively creating something and watching videos are typical activities supporting the flow experience [64].

3.5.2 Flow experience in computer-mediated environments

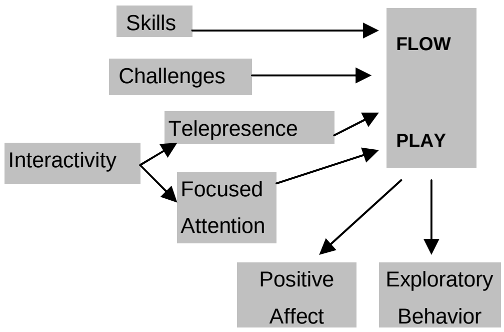

Figure 23: Adapted Version Conceptual Model [16]

The concept of flow and its impact on online marketing has been explored extensively by Hoffman and Novak [168]. They developed a conceptual model that shows the impact of the balance between skill and challenge as well as interactivity on flow and its indirect impact on exploratory behaviour and positive affects (see Figure 23). Their 4 channel model (see Figure 22) shows that flow is directly opposite to apathy and that flow corresponds to enjoyment, positive affect, activation, concentration, creativity [108].

The person-artefact-task model [64] describes the stages of flow, which are flow antecedents, flow experience and flow consequences in a computer-mediated environment (see Figure 24).

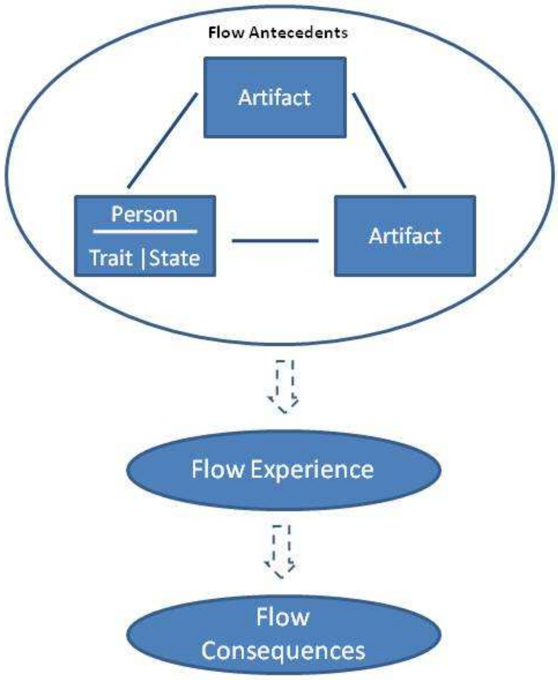

Figure 24: Stages of flow and person-artefact-task model of flow antecedents [64]

In the P-A-T model the description of the person is broken up into a description of traits and state, where the trait is the unchangeable personality and the state describes the dynamic moods of a person. Artefacts are either tools or toys, where tools are things used for external sake [146] and toys are things that bring enjoyment by interaction with them. In computer-mediated environments the artefacts have a more prominent position than outside that context. Flow occurs in a task-artefact interaction as well as in person-task interaction. This basically means that a fit between the tool used to do a task as well as the fit between a person with certain skills and a task that represents a certain challenge can bring people into the flow experience.

Information searching, pure navigation or surfing and reading of incoming e-mail, posted news in newsgroups or web articles are most likely to get people into flow. Chatting is also very likely to lead to a flow experience [26]. Factors that inhibit flow are slow downloads, websites without a clear structure, failures in navigation and searches, advertisements and boring sites that do not change [183].

Flow in computer-mediated environments is based on Csikszentmihalyi's original model of flow [41] (see Figure 21). Some research on flow in website users shows that the flow experience is characterized by time distortion, enjoyment, and telepresence and the factors that affect informal learning most are attractiveness and flow [198]. Flow is most affected by the attractiveness and the speed of the website. In a state of flow users tend to show increased learning activity which leads to a change of attitude and behaviour. The website response speed directly affects the evaluation of the content of the website and through this has an impact on the perceived attractiveness. Attractiveness on the other hand also positively influences how people perceive the ease of use of the website. The main results here are that flow and attractiveness are main factors affecting learning. This seems to contradict most other research on flow in e-learning. The reason could be different user goals in websites with informational content, such as the website used by [198] and dedicated e-learning websites. Behavioural patterns, which ultimately determine flow, are very different in e-commerce and e-learning websites [204]. E-commerce users' activities are predominantly directed towards buying or searching, as well as browsing and knowledge building to support the process of buying. In e-learning on the other hand users look for social and collaborative activities, while learning is the central purpose of the online activity.

3.5.3 Flow experience in e-Learning

The balance between skill and challenge is the starting point of most research on flow in e-learning [194] [176] [131] but there are very different conclusions as to the significance of the skill-challenge balance; some use the balance to measure flow [177] while others use the skill-challenge balance in combination with artefact selection as a means to keep students in the flow [131]. There has been some criticism on the approach to measure flow through skill-challenge and its impact on e-learning when it is based on self-estimation of the skills. Women tend to estimate low skill levels for themselves and this has been related to low self-esteem rather than low skill levels [194].

A result of previous research is that learners show different flow patterns characterised by typical sequences of the different flow states. Learners who are characterized by improving between pre and post-tests are initially in the flow and then move on to anxiety. This group showed signs of flow up to a certain point in the online material, after which most of them moved towards the anxiety area, where their skills are lower than the challenge [177]. These learners tend to give up or leave the website altogether. For instructional design or the estimation of knowledge levels in an adaptive system this can be an indication to better tailor the learning materials at that point.

Flow has been identified as a factor with a positive effect on learning [131] [106] [128] [198]. Flow is beneficial for learning for two reasons. Flow during a task is determined by clear goals, appropriate feedback and a balanced skill challenge ratio. All these factors lead to an enjoyable and intense interaction with the learning materials. Secondly flow experiences are often called autotelic, enjoyable for their own sake. This makes learners come back to experience it again, or at least they are less likely to be distracted by something else, which often is a problem in e-learning [176]. Learners in the flow show more contentment and satisfaction with their learning. Identifying what causes flow provides instructional designers with clues when to use which type of media, e.g. at what time a video is required or when it is just a nice-to-have. Although computer literacy does not affect flow, computer attitude has an effect on learning [106]. Flow experience has been found to show an influence of media content [121]. Flow is independent of age, gender, training experience and computer literacy [131], however it is recommended that learning technologies should be transparent, to avoid that the learner is distracted from learning by technology.

3.5.4 Measurements of flow

There are two main approaches to measure flow: during or at the end of a learning unit. The measurement granularity is critical for both approaches. If it is too fine-grained there is the danger of interruption, on the other hand if the measurement is too coarse-grained it might be biased by individual events, e.g. those closer to the end of the unit. A process measure of flow has to consider both approaches.

Flow has been identified, but without taking a process view, which would enable to detect the progression of flow through a particular activity.

[176] measure skill and balance during and after seven 8 minute long learning units, combined with pre and post-tests to measure learning (see Figure 25).

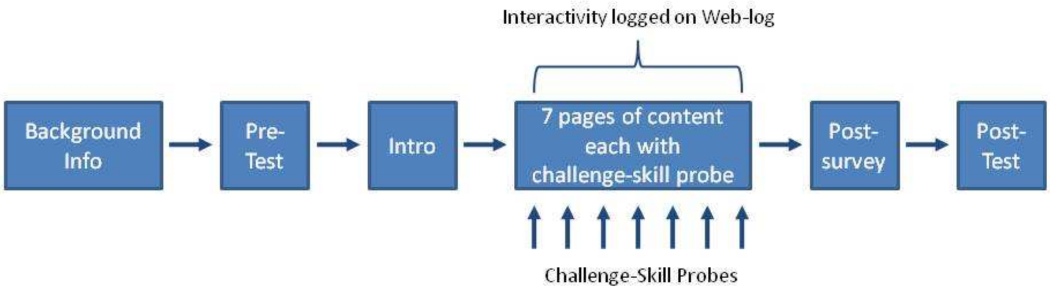

Figure 25: Progress through activity [177]

The skill-challenge probes ask learners for a rating on a 5-point Likert scale after each unit. Interactivity such as page navigation, mouse clicks, activities used and time spent on selected activities is logged. Flow is interpreted as happening when skill and challenge are in balance. The challenge and skill ratings are then cross tabulated with all response pairs, which can then be classified as indicators of anxiety, flow or apathy of the three-channel model of flow. Data from these probes are then taken to describe the flow-path through the activity.

This flow-path is translated into a challenge-skill plot. This can then be used to define a from-flow-distance, which describes how far from the flow-line (challenge/skill=1) a challenge-skill ratio is. The from-flow-distance is shown as signed values, where maximum anxiety is expressed by -1 and maximum boredom by +1 and flow is represented by 0.

The end of session survey consists of a questionnaire with 11 items measuring control, interest and enjoyment. Questions are for example:

- I felt in control of what I was doing
- I was absorbed intensely by the activity

The post survey does not reflect the overall flow experience so much, but rather expresses feedback on outstanding points during the learning path. It is therefore possible to omit the post survey if it is too biased and put more emphasis on the challenge-skill-probes during the learning.

Shin [194] used a post survey with the so-called VFM, or virtual-course flow measure to assess flow with this 5-point Likert questionnaire. The VFM combines questions regarding sub-constructs of flow such as enjoyment, telepresence, focused attention, engagement and time distortion. His VFM is based on previous flow research [74] [198] [168]. In addition to the VFM the method also measures concentration, having a clear goal, skills, challenges and satisfaction. This leads to a very long questionnaire, which produces a lot of data, but which also makes unsuitable for more than once off flow measurement.

Konradt et al. [131] used a multiple-level evaluation, collecting data on flow, quality of experience and training success. This leads to an overall working time of 150 minutes of the participants, which proved to be unfavourable to the overall results. The restrictive and comparatively long learning assessment had a negative impact on the overall evaluation. Lessons learned from the procedure include:

- Learners need autonomy, e.g. free navigation, flexible timing, use of all available functions;
- Combining the learning program with the learning assessment leads to a high degree of standardization, which was seen as negative;
- Length of 2.5 hours per session is too long.

Finally there are the two original methods, the flow questionnaire and the Experience Sampling Method (ESM) which have been developed by Csikszentmihalyi [41]. The flow questionnaire briefly explains the concept of flow and asks participants to describe similar previous experiences. The ESM takes random experience samples over a period of time. Participants get phone calls or a pager gives a signal to report their ratings of their skills and challenges of the activity on a ten-point scale. The original methods have been adapted to online research as previously mentioned assessing the skill-challenge balance [177] as well as replacing the pager by a pop-up window [27]. The pop-up windows were considered as very intrusive by a lot of participants though. These measures can be extended by post surveys either with focus groups [183] or questionnaires measuring enjoyment, concentration, perceived control, exploratory use and perceived challenge [74].

Enjoyment as an important aspect of flow can be measured using the PrEmo method [49] developed in the context of product design (see Figure 26).

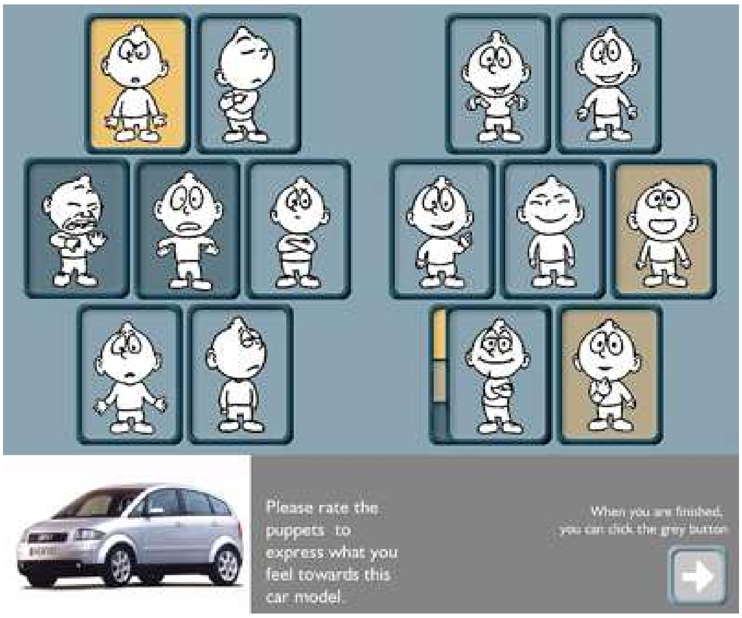

Figure 26: PrEmo Interface [49]

The light-weight method asks at several points of an interaction with e.g. a website for feedback in the form of emotions animated by facial, bodily and vocal expressions. The feedback can get further detailed by a 3-point scale for each of the 14 emotions depicted.

3.5.5 Summary of Flow

Flow has a positive influence on learning and it is determined by clear goals, appropriate feedback and a balanced skill challenge ratio. These characteristics make interaction with learning materials enjoyable. Flow experiences are enjoyable in themselves and keep people involved or makes them come back to have this enjoyable experience again.

The balance and skill ratio can be used as measurable factors of flow in combination with the enjoyment. Challenge and skill probes at the end of learning units can be mapped to a flow path through the learning material. This flow path can also identify break-points for the challenge and skill balance as well as the learners giving up or leaving the page. Measures of enjoyment using emoticons can be combined with the challenge and skill probes. The measure of emotions can give an indication where learners get disengaged. All measures need to be light; they should not be too intrusive or too voluminous.

3.6 Quality of Experience (QoE)

Quality of Experience in e-learning is a fairly new term, not clearly defined yet.

Many of the parameters having an influence on Quality of Experience have been mentioned in previous sections of this literature review. This reflects the complex nature of the concept of Quality of Experience.

The initial problem is to identify a set of parameters big enough to actually contribute to the topic of QoE in adaptive hypermedia and at the same time small enough to enable identification of the most important parameters affecting QoE in the context of e-learning. Existing research often does not consider specifically Quality of Experience in e-learning. This work was motivated by an initial approach for QoE in e-learning [98]. Most other research related to QoE considers partial aspects; perception of multimedia, usability of hypermedia systems, experience in product design or learning experiences in general.

3.6.1 Approaching Quality of Experience – Related Concepts

The trend to innovate faster leads to a more user-centric mentality, but only a few technology companies so far are able to actually anticipate user experience, including the input from lead users from the first development stages. The user experience (UX) or Quality of Experience has been a widely debated and researched area in ICT in general [9] and in e-commerce systems [215] [93] [204] in particular; however in e-learning and particularly adaptive learning systems the discussion about QoE is relatively new [161] [162] [134] and has been approached mainly from a technological or engineering perspective, hence the use of the term QoE rather than user experience.

Quality of Experience in learning systems is starting out with quality in e-learning systems. The structure of the most recent ISO/IEC e-learning standard [114] describes the quality management, assurance and metrics in a general approach. Annex D of the standards first part outlines a reference list of quality criteria.

For the discussion of Quality of Experience sections 3, 4, 7 and 8 are considered relevant. This does not exclude the remainder, but it puts an emphasis on the highlighted aspects. Section three deals with technical aspects; this includes devices and equipment, which have an impact on the Quality of Experience.

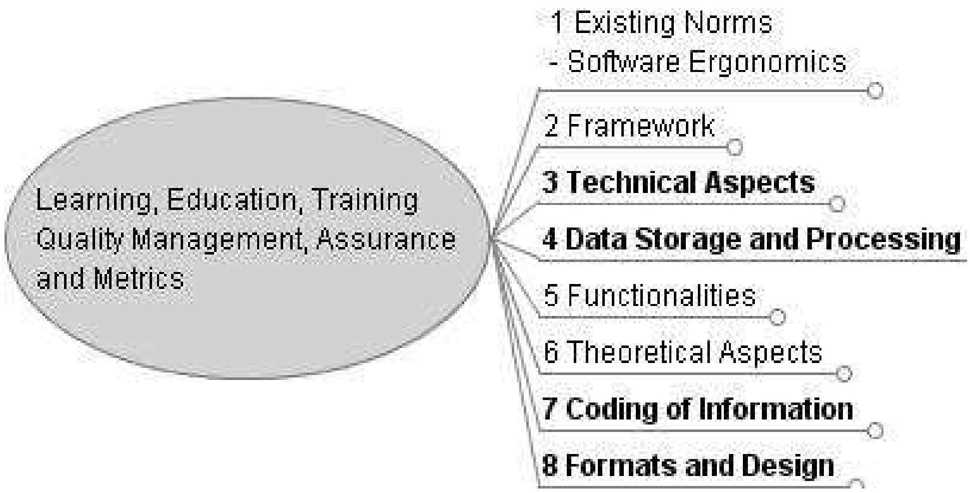

Figure 27: Structure ISO/IEC 19796-1 [114]

Provider related topics include a number of aspects, most often summarized as Quality of Service (QoS) parameters. These are in particular the route of transport to the server, server availability and performance as well as technical support and user data. The fourth section lists three aspects often considered for user and domain modelling in learning systems, namely data specification, visualization tools and analysis. This includes information about exercises, learning period and hyperlinks, learning progress, user-defined analysis, previous knowledge, system control, adaptation and control of learning results. Section seven considers coding of information, which includes many of the QoS related aspects, such as the quality of images, technical aspects, speed, zoom and change of perspective. Here we also find considerations of didactical aspects. Section 8 considers different media types and formats.

In industry the concept of Quality of Experience is approached with a clearly defined goal: to find the level of user experience (UX) suitable for a certain target market. The level of user experience describes which features the customers will actually notice and value or features the customers will miss if eliminated. The components of user experience in regard to product interaction as outlined by Beauregard and Corriveau [9] explain how product interaction influences perceptions, which cause emotions and thoughts and influence attitudes. This eventually influences intentions and the interaction with a product. It provides starting points for measurement of user experience that can be transferred to other user experience contexts.

A basic model for UX [10] outlines the main components (see Figure 28).

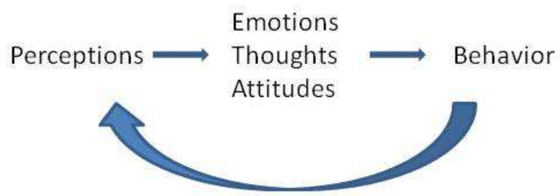

Figure 28: Components of User Experience [9]

Perceptions of the user shape the emotional impact, thoughts and attitudes towards a system. Perceptions relate to the process of acquiring and interpreting information and can be influenced by video or audio quality. Emotions cause positive and negative feelings, trust and mistrust, which impacts on the user in a learning context [6] and the motivation of the learner. Attitudes are judgments about a target. This relates closely to the concept of goal-orientation [41] [217] in learning theory. A clear goal depends on the attitude of the learner. The learner behaviour is a result of the combination of emotions, thoughts and attitudes and forms the learning experience. This brings the concept of UX close to Dewey's theory [51], which also points out that experience build up upon one another, each experience affecting how the learner will experience the subsequent situations.

QoE is not clearly defined. The more technically-oriented put it in close proximity to the concepts of QoS and QoP [196] [34] [80] whereas the more customer/product-oriented produce a variety of different meanings relating to experiences [68] [48] [178]. The QoE model, which is introduced in the next chapter, emphasizes the combination of technical, experience-dependent and context-dependent aspects. In our scenario of e-learning the technical aspects are summarized as QoS parameters, experience-dependent aspects are captured by flow, while learning is the context of the application.

Quality of Experience is defined by ITU [117] as the "overall acceptability of an application or service as perceived subjectively by the end-user." Previous research on QoE in multimedia e-learning considered the end-user expectations for QoS [163]. In an attempt to combine aspects of end-user perceived QoS and experience an arbitrary combination of end-user perceived QoS, usability and QoS has been proposed [105]. This view is broadened by a concept of QoE that introduces the roles of user and customer and differentiates between Quality of Experience (QoE), Quality of User Experience (QoUE) and Quality of Customer Experience (QoCE) [126]. This increasingly user-centric perspective has been developed further by Wac [218], who additionally considers the criticality of the application to the user's context. This multi-dimensional character of experience is relates to the human-computer interaction concept of experience [68]. This concept has been taken up in the context of funology and the differentiation of designer and user perspective was added [93]. The focus has now moved towards inclusion of subjective as well as objective aspects. Subjective aspects cannot or only with great difficulty be influenced. This conveys that experience cannot be purposely designed; design can support an experience though [227].

3.6.2 Measurements for QoE in e-learning

Each component of user experience requires specific measures [9]. To investigate the relationship between video quality and user experience the combination of three methods, expert assessment, non-expert assessment and objective measures, follows an ITU assessment recommendation [118] and uses bit rate as an independent variable. This high-level experimental design for user experience can also be applied for QoE research.

Perception of any information system is highly influenced by technology change. User experience adapts with changes in technology; the better the average experience the higher the expectations for future use. An assessment of computer literacy can provide some insight on the user perception and enable an estimate of the user's expectations. The previously outlined methods to evaluate QoP also provide relevant information.

Emotions can be measured with a combined assessment using quantitative assessments, Likert-type questionnaires and case studies. One quantitative approach developed by Desmet [49] measures emotional response by means of emoticons resembling 14 basic emotions.

Attitudes can be described as function of expectation and past experiences [93]. The grounded theory technique is one suitable way to assess attitudes, and appears to be more suitable than commonly used methods such as interviews based on Likert-type scales or simulations [10]. These last two methods are prone to contain a strong bias due to unclear attributes and questions or context which is not representative.

Behaviour changes for users of e-learning systems can be measured using level 3 of Kirkpatrick's training evaluation model [127]. The first level of the model evaluates student reaction. It looks at relevance of the objectives, the ability of the course to maintain interest, the amount and appropriateness of interactive exercises, the ease of navigation and the perceived value and transferability. Level 2 assesses the increase in knowledge or capability and assessment often consists of a pre-test and a post-test. Level 3 asks for feedback regarding behaviour changes, which deals with the question whether any of the learning results assessed in Level 2 have moved from short-term memory to long-term memory and found its way into everyday routines.

This research design has been implemented to relate technical performance to user experience and to model different QoE dimensions such as the effectiveness of an application, its efficiency, usability, the expectations and the context. Different QoS and QoE probes combined with pre and post-usage questions (see Figure 29) provide results that show how the different parameters influence QoE [48].

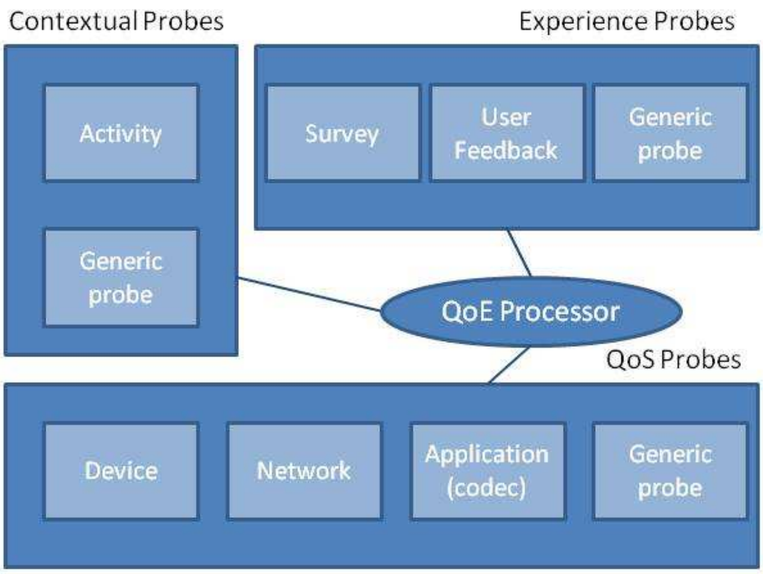

Figure 29: QoE probe model [48]

The different aspects can also be divided into measurable and non-measurable factors for the QoE of multimedia services, where the measurable factors include software and hardware, QoS parameters, codec and content evaluations. The non-measurable or subjective factors include QoE parameters, expectations, understanding, satisfaction, attitude and habit. These factors can be translated into an XML document where each parameter can be associated with discreet values, which are constrained in an XML schema, representing a metric of each parameter [179].

3.6.3 Ways to improve Quality of Experience in multimedia e-learning

Research on Quality of Experience for text and image-based documents shows, that learners perceive an improvement of their learning experience if the download times of the learning materials stay within a certain threshold [98]. Download times can be manipulated by changing the size of the files in two ways; either downsizing the image resolution or simply reducing the number of images on a page. Results show that display resolution and processing speed reduced study session time [161], which has an impact on Quality of Experience.

People in flow perceive clear goals and feedback more easily and flow helps students to become absorbed in challenging tasks. Providing opportunities to take the initiative in learning can help them to experience learning as an enjoyable experience [226]. Intrinsically motivated students progress better in their area of talent and their performance is positively related to enjoyment of their work [226]. These two aspects seem to indicate that giving students the option to choose how to learn can improve the Quality of Experience.

3.6.4 Summary of Quality of Experience

Different QoE models contain different parameters. A lot of them have in common to differentiate between QoS parameters, which are measurable with standardized procedures and experience related parameters, which are more complex and require less straight-forward measurement methods such as pre-post questionnaires, emoticons to assess emotions, and learning assessment.

QoE measurement overlaps with QoS, QoP and flow measurement, because it combines aspects of all these areas.

3.7 Summary

The literature survey explored basic technologies and theories relevant for a Quality of Experience model for multimedia e-learning. It investigated different approaches to the concept of Quality of Experience and compared it with the concept of user experience. A number of factors were identified that are likely to impact on QoE in adaptive multimedia e-learning systems which can be attributed to the different aspects and a holistic view on QoE considers different roles of the learner as learner, user and customer. The user role is mainly affected by usability and flow experience, the customer role is mainly affected by aspects of Quality of Service and the learner role is mainly affected by learning aspects. Figure 30 gathers the various factors contributing to Quality of Experience.

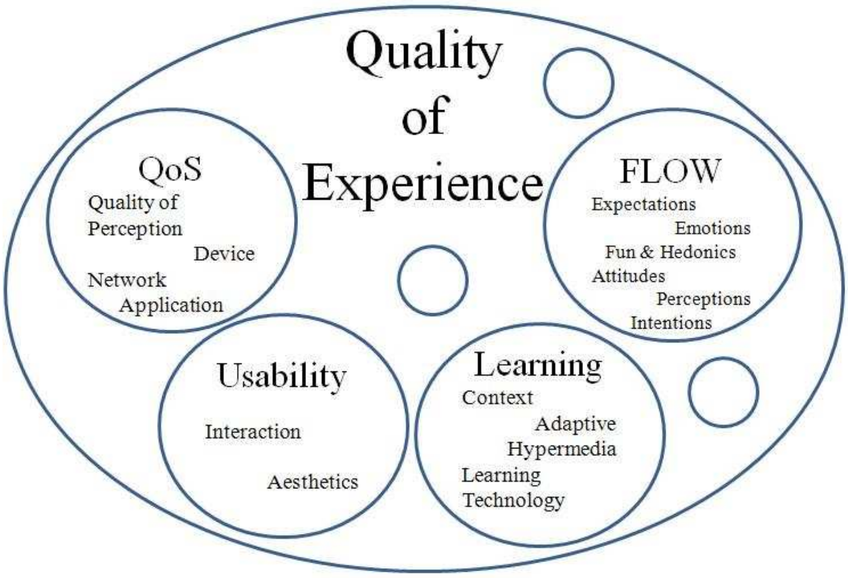

Figure 30: Aspects of Quality of Experience

These factors serve as a matrix for a list of hypotheses which summarize the findings from the related work. The commented list of hypotheses is provided as part of the Delphi study in chapter 5.

In conclusion QoE is affected by four main factors, QoS, flow experience, learning and usability. From research we know that users' QoE is affected by expectations about quality parameters such as QoS or learning results. Previous research on QoE in adaptive e-learning focused on the impact of QoS on download times and in turn on task completion and its impact on QoE [98]. Expectations about usability have to be recognized as a factor of QoE, but it is not included in the adaptation this research reports as this would open a completely new area of research beyond the scope of this project. Additionally usability is considered a prerequisite for a discussion of Quality of Experience. Similarly a QoE model has to consider the provision of a selection of material suitable to learner knowledge level and learning goals, as well as different means to interact with learning content.

4 QoE Design

4.1 Introduction

The QoE model proposed for adaptive hypermedia systems considers three roles of the learner: learner, user and customer. The learner does not always take on all these roles simultaneously, but they all affect the Quality of Experience.

In e-learning the *learner* role is the most obvious, however the remaining two roles are important as well. The learner has expectations regarding delivery mode, learning activities, teaching models and learning outcomes. Delivery mode can be fully online or blended learning with face-to-face classes. Typical learning activities are knowledge transfer, learning tests, assessments and exercises. Depending on the teaching model the role of the learner is changing from a dependent student in a teaching scenario to a self-directed learner. The main objective of the learner is to reach her learning goals.

However the learner as *customer* has expectations regarding benefits from using the system, which are formed by previous experiences with other web-based systems. Input into the system, monetary or time-wise, has to generate benefits. The benefits can be learning outcomes, meeting peers in a study group, getting access to information or accreditation of learning outcomes. Expectations of the customer also include system performance, for example QoS, or added-value e.g. learning to use new tools or new technologies. Customer expectations also vary, depending on the context. Expectations will be higher regarding a commercial system than for a non-commercial system; e-games systems raise different expectations than e-commerce or e-learning systems. Experience in particular with e-games raises expectations that systems provide an enjoyable and engaging online experience. The customer wants to know what the benefits are of using e-learning systems and expects an enjoyable experience.

Users of the different web-based systems have expectations that vary in detail, but not in general. Following conventions and standards helps meeting these expectations. Conventions exist for example for navigation, login or upload of documents. Usability following Nielsen's [165] heuristics and Krug's [132] paradigm are expected of websites. A website which is difficult to understand or unclear about what to do on the website will cause disappointment. Users are familiar with certain communication tools and collaboration tools and will expect email, a blog or a forum for communication, and a wiki, a forum and multi-user tools such as an online write board or Google docs for collaboration. The user expects an easy to use system.

To consider all three roles the QoE model considers four main factors, QoS, flow experience, learning and usability. The following section on the QoE model outlines the main relationships of different factors. The adaptation policies describe an approach to implementing QoE adaptation and the QoE probe model summarizes which parameters and measurements are considered for the adaptation. Finally a scenario for implementation is outlined as QoE system design. This chapter describes how the QoE model evolved and therefore anticipates a summary of the results of this research.

4.2 QoE Model

The QoE model acknowledges that QoE is different for every person, which requires the system to be able to include feedback and adjustment from the user. The focus of this research was to investigate the impact of QoS on QoE in adaptive multimedia e-learning systems.

The QoE model is based on the assumption that QoE in adaptive multimedia e-learning systems is determined by learning and the flow experience; and that both are affected by QoS parameters (see Figure 31).

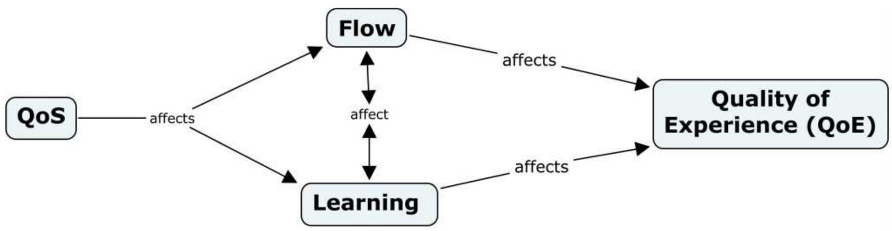

Figure 31: Proposed QoE Model

The QoE model in Figure 32 includes those factors initially considered relevant on the basis of the literature survey. The metrics I chose to study in detail are highlighted in bold. These are multimedia learning, skill and challenge ratio and interaction. They represent the subset of the metrics that are most influenced by changes in QoS.

Learning and flow experience are both directly affected by QoS. QoS is based on network and application parameters. The network parameter considered is available bandwidth as it is the parameter most relevant as defined in chapter 3. The applications considered are video, audio and text. For the adaptation policies, the changes in QoS generate the impulse for the sequence of media types. If the QoS indicates good network conditions, the system can provide any of the media formats, if conditions worsen, the selection will be reduced. In combination with requirements for a mix of media formats, the QoS sets the pace for the sequence of media types. Changes in QoS therefore affect the learning process as well as the flow and in essence determine the Quality of Experience.

Learning and flow experience can be directly influenced by a mix of different media, but also the type of interaction, feedback, a clear set of learning goals and a suitable ratio between learner skills and challenges. Feedback from the system can be provided on the progress in the course and assessment results. Usability of the learning system affects QoE, but is not influenced by QoS. Hence, we chose not to include it directly in our inquiries. However, care was taken in developing the user testing material to ensure a reasonable level of usability.

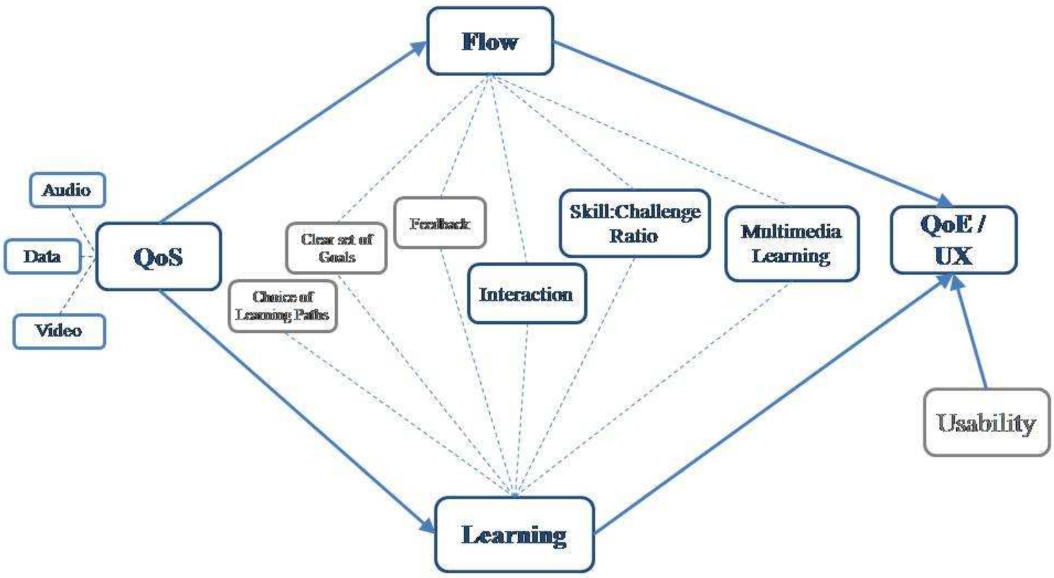

Figure 32: Expanded QoE model

In the course of the research the factors affecting QoE were adjusted. The final QoE model is shown in Figure 33and reflects the conclusions from the research.

The arrow richness indicates the relative strength of the impact on other aspects of the model; it is not a detailed representation. A significant direct impact of QoS on experience could not be confirmed. Yet the results show that QoS affects flow and learning. The impact of QoS on flow is much stronger than the impact on learning. A known reciprocal effect between learning and flow could be confirmed. It is of similar strength to the impact of QoS on flow. Learning, flow and usability were found to have the strongest effect on experience. Usability is included in the model, because of its strong impact on experience, but it has to be pointed out that no impact of QoS on usability was found.

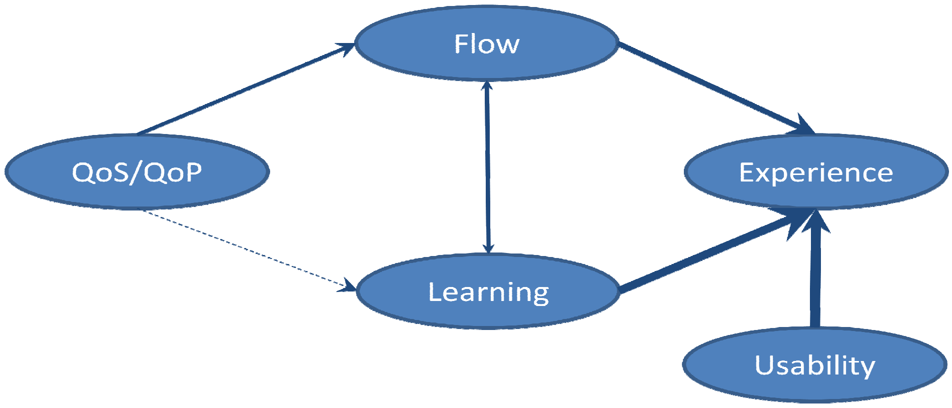

Figure 33: Final QoE model

4.3 Adaptation Policies

The decision of what material to present to the learner is based on a combination of constraints from the technical environment of the learner and multimedia theory.

The policies considering QoS and media and can be summarized in a two-step process: the assessment of network conditions is the first step, followed by the evaluation of the media history, and can be summarized as the QoE strategy (see Table 8).

The adaptation considers available bandwidth, which reflects network usage. High network usage will result in poor available bandwidth and vice versa. As mentioned beforehand, the adaptation only considers available bandwidth as it is the parameter affecting most other network parameters as well. Including some of the remaining parameters, e.g. delay and jitter, would require a fully implemented, more complex algorithm. One goal of this research is however, to show the strong impact of the adaptation to available bandwidth on the learner experience and that the adaptation will improve learner experience considerably.

For the assessment of the network conditions the bandwidth is classified as poor, medium or good. The classification is not adjusted to a specific value, as audio and video files can vary considerably in their needs for available bandwidth. Poor bandwidth means that all of the available resources except for text require more than the bandwidth that is available and only text can be sent. Medium bandwidth allows sending text as well as audio resources and good bandwidth allows sending a video, an audio file or text.

Table 8: QoE Strategy

Bandwidth	**Suggestion**	**Previous Media**	**Recommendation**
POOR	Illustrated text	Any	Illustrated text
MEDIUM	Illustrated text Or Audio	Video	Audio
		Audio	Illustrated text
		Illustrated text	Audio
GOOD	Audio OR Illustrated text OR Video	Video	Audio
		Audio	Illustrated text

The assessment of the network conditions results in a list of suggestions. This list contains all learning resources of all media types for that particular knowledge level, suitable to given network conditions. For very good network conditions this will be video, audio and text, for bad network conditions only text resources will be available.

The second step takes the list of suggestions, checks them against media history and results in a recommendation that avoids immediately repeating the same media type, while selecting the resource with the highest bandwidth demands.

Figure 34 shows how this 2-step algorithm is embedded into general adaptation steps, which also consider knowledge level and course delivery.

The algorithm combines quality of service to maintain a media mix and is called Quality-Adaptation for Media Mix (QAMM) algorithm. It is called QAMM2 if course delivery is based on the recommendations, meaning both steps of the algorithm as introduced above are considered. If only a QoS-based suggestion is considered it is called QAMM1, meaning the second step considering media history is omitted and course delivery will be based on the suggestions. QAMM1 will deliver the media with the highest bandwidth requirement that can be sent based on available bandwidth. QAMM2 seeks to enforce a rotation of media types from video to audio to text, while respecting the QoS bandwidth restrictions.

The QAMM algorithm can be embedded in a larger adaptation algorithm (see Figure 34).

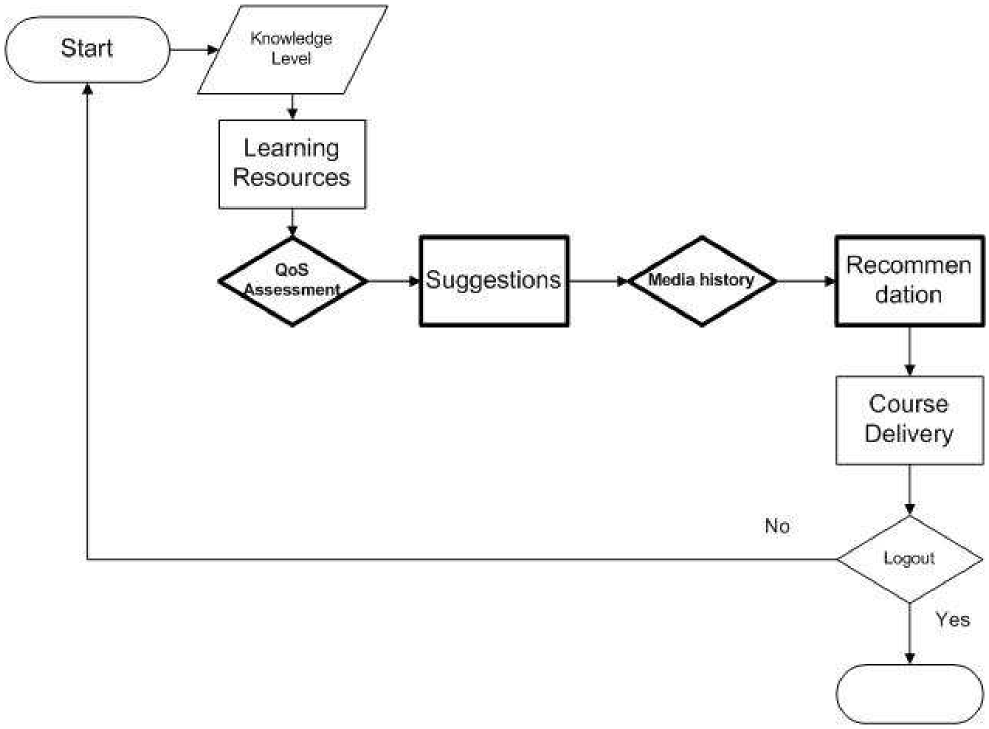

Figure 34: Algorithm flowchart

For example data about the knowledge level determine the learning resources as a first step, followed by the two-step QAMM algorithm as outlined above. It concludes with a recommendation, followed by the course delivery.

Based on the media mix, the algorithm can respond to network congestion to some extent following the media type and transmission policy outlined above, which selects the media type depending on the transmission resources.

4.4 QoE Parameters and Measurements

To determine the QoE several measurements are required, reflecting the QoE components from the QoE model. Building on Deryckere's model [48], which has been discussed in chapter 3, the probe model consists of learning probes, experience probes, QoS probes and usability probes. The QoE probe model replaces generic probes from Deryckere's model with specific probes required to determine QoE in e-learning (see Figure 35).

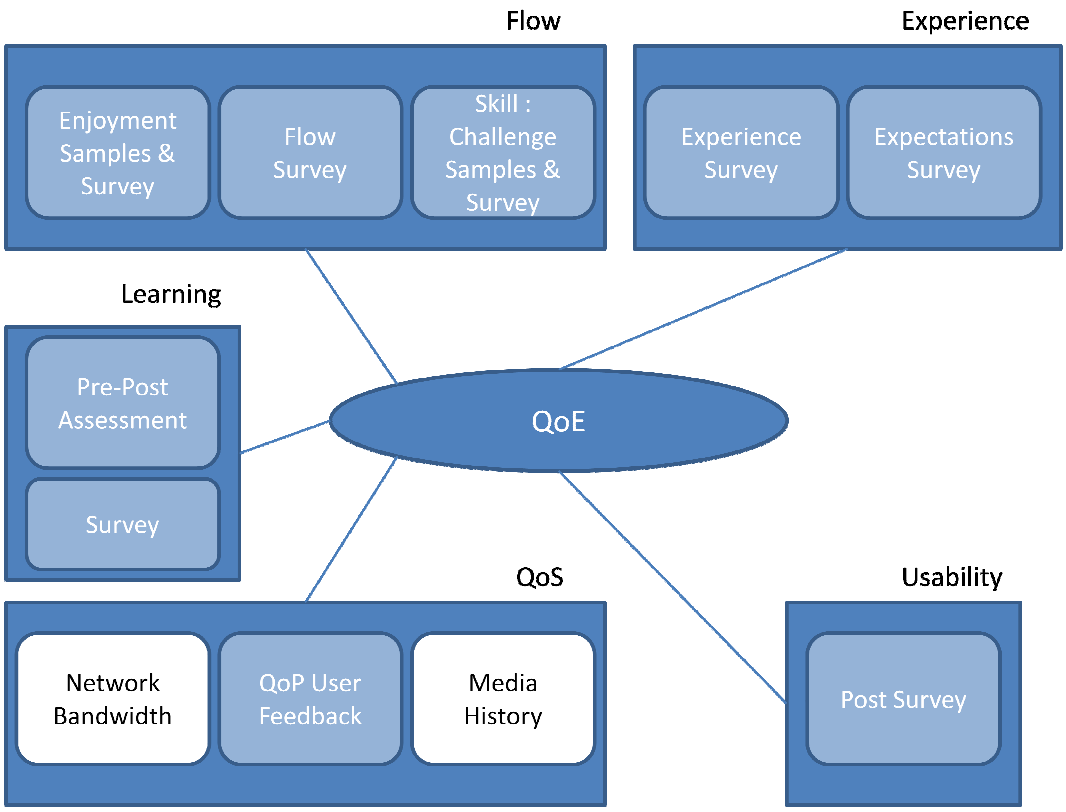

Figure 35: QoE Probe Model

The learning probes are pre and post learning assessments and the post survey. The pre-post assessment assesses the knowledge level at the start and at the end of the course. The post survey collects feedback from the learner about perceived learning outcome.

Experience probes include probes for overall experience and an expectations probe.

Flow is measured with a short user questionnaire at the end of each unit. To assess flow it includes questions regarding skill and challenge levels, time distortion and general experience following Pearce's probe model [177]. Additionally emotional response is considered using a set of emoticons taking enjoyment samples, following Desmet's PrEmo [49] approach.

Usability was initially not considered, but during the pre-test sessions it became obvious that usability would be an issue, despite using a system that is in use in many universities. Usability was assessed with the post survey and monitored during the course with observation and the user chat.

QoS probes in an adaptive system would include probes for network bandwidth, QoP user feedback and media history. Network bandwidth and media history probes are omitted for the Wizard of Oz user studies [122], because their impact is the object of investigation and they are therefore not probes, but controlled variables. QoP is measured with the short unit questionnaires, collecting feedback on the QoS perceived by the learners (QoP) after each audio or video concept.

The progress through the course and the probing is summarized in Figure 36. This model of the progress through the course aims to capture data at all stages of the user interaction and is based on Pearce's model [176].

The pre and post-tests were developed in cooperation with DCU language service and are very similar to tests used by the language school to evaluate students' level of English. Enjoyment samples and unit questionnaires are very light tools and were integrated in the course design. The same can be said for the pre- and post-assessment at the beginning and the end of the course.

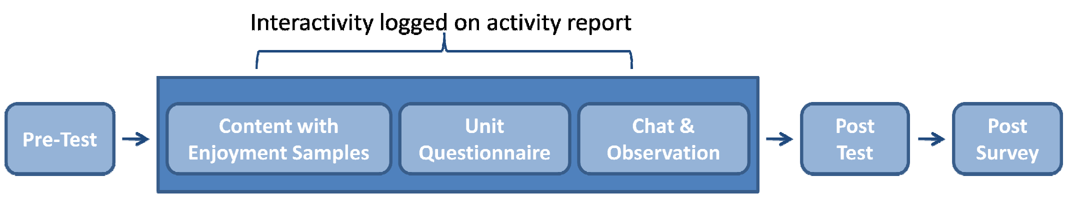

Figure 36: Progress through course

4-point Likert scales were used for the enjoyment samples, while the unit questionnaires applied 5-point Likert scales. The post survey used 4-point Likert-type scales. Page visits are considered if they are within a time range relating to page content.

The probe model aims to cater for the different learner roles introduced at the beginning of this chapter and are particularly catered for by the following. The learner is considered with learning probes and the skill and challenge probe; the user is taken into account with usability and QoS probes while the customer is recognized with the enjoyment samples.

4.5 QoE System Design

The focus of this research was to identify factors that influence QoE. The model, policies and measurements described above were developed and tested using simulations and Wizard of Oz user studies [122]. Implementation of an actual system using existing adaptive platforms was not aimed for; because adaptive platforms do not convey the impression of a professional learning management system to the user [95] and this would introduce an unwanted factor affecting QoE. However, the following section describes how implementation can be achieved, using a number of existing tools and considering recent research results in related areas.

For proof of concept for the results of this research I successfully collaborated on work that established the feasibility of authoring the QAMM2 adaptation strategy in an adaptive system [190]. The merging of strategies, e.g. strategies for media mix and QoS adaptation, has been successfully tested with My Online Teacher (MOT), an authoring system for adaptive hypermedia [70]. Whurle [153] represents another approach and combines web services with an LMS framework. QoE adaptation can be added as a web service.

All adaptation services or platforms mentioned above include a user and domain model. The main parameter that needs to be constantly collected from outside the system to enable the QoE adaptation is the available bandwidth. This can be done using tools such as a media player or a browser plug-in. Examples are the *ambulant player* [17], an open-source media player with support for SMIL, enabling bandwidth estimation or *flowplayer* [66], an open source video player with built-in bandwidth detection.

Integration of the adaptive platform into a learning management system is the final step. The combination of LMS and adaptive platforms or services has been achieved in several projects. *AHA!* has been integrated in Sakai [73] and an adaptive personalized e-learning service (APeLS) has been incorporated in Moodle [212]. Alternatively the Adaptive Display Engine [188] supports execution and combination of different adaptation strategies.

4.6 Summary QoE Design

The QoE model combines the impact of QoS-related parameters on learning and flow and consequently on the Quality of Experience. Adaptation policies describe how to enforce QoE adaptation. A set of parameters and measurements to determine the QoE are summarized in the QoE probe model. The final QoE model summarizes the results and visualizes the different impacts of the factors on QoE. Proof of concept has been achieved with collaborative work on authoring of adaptive strategies.

5 Delphi Study

5.1 Introduction

The initial literature review in chapter 3 shows that QoE has been a widely debated and researched area in ICT in general [9] and in e-commerce systems [215] [96] [204] in particular; however in e-learning and particularly adaptive learning systems the discussion about QoE has received little attention [162] [134]. Previous experience of the learners as user and customer in a variety of (multimedia) e-commerce and entertainment systems raise and form their expectations for other online applications [167]. These different relationships as learner, user, and customer, in the end all influence the Quality of Experience (QoE) of the learner. The experience of the learner determines learning results as well as drop-out rates and retention in e-learning [137]. Enhancing the QoE and avoiding high drop-out rates requires a better understanding of the concept of QoE. Based on the literature survey, QoE in adaptive multimedia e-learning can be defined as the sum of flow experience and learning with QoS impacting both aspects [157]. However, there is no consensus regarding the definition for Quality of Experience in multimedia e-learning. Based on the literature review, I identified a number of hypotheses regarding the factors that potentially affect QoE. I conducted a Delphi survey of experts to determine their views regarding these hypotheses.

5.2 Method

A Delphi study is a way to identify any consensus in an expert group and clarifying what agreement exists [140]. The Delphi study consists of iterative rounds of a questionnaire which is completed by the expert panel. The questionnaires for rounds 2 and higher contain feedback on the results of the previous rounds from all experts. A web-based survey [3] can be used, as it is time and cost-efficient and can quickly reach a bigger panel of suitable, but geographically dispersed participants. Since the quality of the study results depends mainly on the feedback of the participants, the selection process of the participants in the study has to be quite rigorous. If the panel selection has been sufficiently thorough, a panel size of 15 to 20 is quite sufficient [88]. Research guidelines for the Delphi study [94] provide detailed instructions on the main issues to consider in constructing the study.

This Delphi study was conducted to investigate ranking and agreement levels on a list of 17 hypotheses regarding the Quality of Experience for users of adaptive multimedia systems which were identified by the literature review in chapter 3. The literature review focused on recent research in the areas of flow experience in online systems, Quality of Service (QoS) in relation to e-learning, learning theory in e-learning, usability or user experience all in relation to Quality of Experience (QoE). The agreement levels of the Delphi expert panel was complemented by a ranking of the hypotheses in terms of importance. A web-based Delphi study was carried out and comparative statistical testing applied.

The Delphi study was preceded by interviews with an advisor panel consisting of five experts. The advisor panel was consulted to refine the hypotheses included in the questionnaire and afterwards the three round web-based Delphi study followed. In the first round of the Delphi study the expert panel was presented with 17 hypotheses and the importance evaluation from the advisor panel.

The Delphi expert panel was invited following a selection pattern [2]. The selection criteria were years of expertise and current high-quality publications in any combination of the following areas: user experience and usability; personalization, social media and community informatics; software engineering, multimedia engineering; or e-learning, training and teaching. In total 70 experts were contacted by e-mail, of which 33 replied stating their interest in participation. A heterogeneous sample of 31 experts initially participated in the study. A breakdown of the panel is given in Table 9.

Table 9: Characteristics of expert panel

Gender	*n*	Area of Expertise	*n*	Research, Industry, other	*n*	Country	*n*
Female	14	User experience and usability	6	Research & Teaching / Academic	7	Austria	1
Male	17	Personalization, social media	5	Industry Research / Industry	8	Switzerland	1
		Software Engineering	3	Research	10	Germany	15
		Multimedia Engineering	3	Training & Education	6	Ireland	4
		E-Learning	6			Netherlands	1
		Training, teaching, knowledge management	8			UK	5
						US	4

Each of the three rounds of the survey was accessible to the panellists for three weeks. An invitation was sent out by e-mail, then reminders were sent ten days after start of each round to those participants who had not replied, and finally, reminders were again sent four days before the end of the round. Panellists who did not respond were not invited to participate in the next round. The number of panellists went from 31 in round one, to 27 in round two and 25 in the third round. This means the number of participants stayed well above the previously outlined required numbers for participation. The invitation letter can be found in the appendix.

In the first round the participants were asked to provide their agreement on a 3-point Likert scale labelled “I agree”, “No opinion”, and “I disagree” and comment on each hypothesis if desired. In the second and third round the participants were asked to provide their agreement on a 5-point Likert scale labelled “I strongly agree”, “I agree”, “No opinion”, “I disagree” and “I strongly disagree” and comment on each hypothesis if desired (see Table 10) and finally rank the hypotheses in the order of importance. The scaling method for agreement has been taken from Delphi procedures used in previous studies [109] [46] [84] [35].

Table 10: Example of layout as presented for Hypothesis 1, Round 2

Hypothesis 1: Applying conversation style texts corresponds with more intense learning for beginners.	
Summary of feedback from all participants	Comments
	Doubts
	Percentage of agreement in Round 1
Agreement	□ Strongly agree
	□ Agree
	□ No opinion
	□ Disagree
	□ Strongly disagree
Comments	

Between rounds feedback was analysed using content analysis [32]. Content analysis uses qualitative, verbal information and transforms it into quantitative data. In this research the comments of the panellists are categorized and summarized and added to the section of the respective hypotheses and given back as a statement. For all three rounds of the Delphi study, quantitative analysis included percentage response rates and percentage for each level of agreement for each statement. For rounds 2 and 3 only, analysis also included median rank, range of selected ranks and their associated group rankings, using Spearman's Rho to compare agreement on the importance rankings between rounds 2 and 3 as well as 1 and 3. For rounds 2 and 3 statements are rephrased, adding the feedback from the previous rounds and the percentage of agreement or median rank value from round 2 and 3 respectively. For the ranking, the median and mean values show the group aggregate rank, while range and standard deviation (SD) show the spread around that result. If the range and SD are large, they indicate disagreement.

Decision about the ranking at the start of rounds 2 and 3 was based on average rank in the previous round. The percentage of agreement was considered for ranking ties. The hypothesis with the higher agreement percentage got the higher rank.

The stability of the panel decision was analysed by Spearman's Rho and Kendall's Tau [228] [110]. The higher the values the more consistent is the ranking. Spearman's Rho is a correlation coefficient for ranked data. It can range from +1 to -1, +1 representing perfect positive correlation, -1 representing negative correlation. The values for the study rounds show whether the expert panel changed its mind on ranking the hypotheses between rounds. Kendall's Tau, or the rank-correlation coefficient, also identifies the correlation between two sets of rankings. The Tau value shows the probability for a set of hypotheses being ranked in the same order twice, rather than in a reverse order.

The study was concluded when consensus on ranking, identified by a Rho of >0.8 and a Tau >0.7, was reached. A Rho value of 0.8 was chosen, because it can be found in the literature as a high correlation value [83]. The value for Spearman's rho is chosen slightly higher than Kendall's Tau, because Spearman's Rho usually produces higher values than Kendall's Tau [63].

5.2.1 Advisor Panel Interviews

The goal of the expert interviews was to discuss initial hypotheses drawn from the literature review in chapter 3 and to check whether the hypotheses were relevant, clear, unambiguous and non-leading. The hypotheses are provided in the following subsection. The selection of the experts followed the same criteria as the panel selection later on. The experts involved in the interviews were not invited for participation in the Delphi study. At the start of the interview the experts were provided with the proposed QoE model [157] and a short definition of the main concepts (see Table 11). The interview guidelines are provided in the appendix.

Table 11: Concepts used in advisor panel interviews

Concept	Definition/Description
QoE	An e-learner's Quality of Experience (QoE) is informed by previous experiences as a learner, a user of computer/web-based systems, and a customer. We propose a holistic view on QoE, considering the different roles of the *learner as learner*, *user* and *customer.*
Flow	The concept of flow was first introduced by Csikszentmihalyi and it represents the optimal experience or complete absorption with an activity. It is characterized by 8 dimensions, which can be divided into three stages: antecedents, experiences and effects. The dimensions allocated to the antecedent stage are a clear set of goals, immediate feedback and equilibrium between challenges and skills. The experience stage is characterized by the merging of action and awareness, focused concentration and a sense potential control. The final effects stage is characterized by a loss of self-consciousness, time distortion and a self-rewarding experience. Flow has also been described as a match between skills and challenges, and depending on the match or mismatch, it results in flow, boredom or anxiety.
Learning	Learning is characterized by learning and teaching methods, learning styles, different learning theories, the quality of feedback and interaction influence as well as the ratio of skills and challenges.
QoS	The interdependence of network-level parameters and media type defines the relevance of the QoS elements. Delay, jitter and loss can be highly disadvantageous for the QoE, but they can also enhance the QoE. For example a video-based presentation can have a better QoE, if the loss of frames keeps some pictures longer available while the audio information continues, because it provides more time to take in the visual information.

Information for the interviewees included a brief outline of the research design, to give the interviewees some indication how their input would be used later. Advisors were asked to give general feedback to the different hypotheses and indicate how they evaluate the importance for the concept of Quality of Experience. Most hypotheses were slightly rephrased or extended in the process, making them clear and unambiguous. One hypothesis was deemed to be very similar to another hypothesis and was omitted in the Delphi study. In the course of the interviews three more hypotheses were added. The advisors were asked to submit an importance evaluation for later comparison with the final rankings of the Delphi study. Importance was classified in three categories, A, B or C, very relevant, relevant, and irrelevant. The list of hypotheses is provided with the interview guidelines in the appendix.

5.3 Results

This section describes how consensus developed through rounds 1 to 3 of the Delphi study, considering

- Agreement percentages
- Importance rankings
- Mean, median, range and standard deviation (SD)

A brief comparison between the advisory panel evaluations of the hypotheses and the final ranking of the Delphi study provides an introduction into the results.

5.3.1 Results Advisor Panel Interviews

Four of the advisors on the panel provided their importance evaluation. The comparison between the final rank and the evaluation of the advisor panel (see Table 12) shows similar results, with a few exceptions.

The hypotheses with final rank 1 received a mediocre evaluation of ABBC. The hypothesis with the final rank 5 received A from all advisors. More surprisingly the hypothesis finally ranked fifteenth in the Delphi study also received A from all four advisors. The hypothesis with the lowest evaluation from the advisors (ACCC) was ranked eleventh.

Table 12: Comparison Final rank vs. Importance evaluation

No.	**Final Rank**	**Importance evaluation**
H9	1	**A, B, B, C**
H7	2	A, A, A, C
H6	3	A, A, A, B
H16	4	A, A, A, B
H3	5	A, A, A, A-B
H5	6	**A, A, A, A**
H15	7	A, A, A, B
H13	8	A, A, A, B
H4	9	A, A, A, B
H1	10	A, A, A, B
H12	11	**A, C, C, C**
H8	12	A, A, B, B,
H14	13	A, A, A, B
H17	14	A, A, B, B
H2	15	**A, A, A, A**
H11	16	A, B, B, C
H10	17	A, A, B, B

In summary it shows that the advisor results are mainly confirmed by the Delphi panel results. They disagree on the importance of the impact of ease of use of the learning environment on the interactivity with the system (H12). The possibility to use still images with audio replacing a video (H15) was also a hypothesis evaluated very differently. The relevance of setting learning goals (H6) and the impact of ease of use of the learning environment on flow (H9) was evaluated almost contrarily. Interestingly the advisors considered the hypotheses relevant which were ranked last throughout the three rounds of the Delphi study.

5.3.2 Results of the Delphi Study

The results of the final round are presented in Table 13. It shows the final ranking of the hypotheses and the percentages for agreement and disagreement.

Table 13: List of Hypotheses

Final Rank	**Hypothesis**	**Percentage Agreement / No opinion / Disagreement**
1	Better ease of use of the learning environment corresponds with clearer focus of attention. (H9)	96 / 4% / 0%
2	Ongoing system feedback about progress results in more intense learning. (H7)	88% / 12% / 0%
3	Providing a choice between a linear course structure and an open learning environment improves learning results. (H6)	80% / 12% / 8%
4	A more intense flow experience corresponds with improved learning results. (H16)	84% / 12% / 4%
5	Learning materials providing a mix of different media lead to improved learning results. (H3)	84% / 8% / 8%
6	A clear set of learning goals outlined by the system corresponds to improved learning. (H5)	84% / 8% / 8%
7	Improvement of QoS when delivering various multimedia types can improve the flow experience. (H15)	92% / 8% / 0%
8	Increased attractiveness of a learning environment enhances flow. (H13)	96% / 4% / 0%
9	A balance of skill and challenge managed by the system corresponds with increased learning. (H4)	96% / 4% / 0%
10	Applying conversation style texts correspond with more intense learning for beginners. (H1)	68% / 8% / 24%
11	Ease of use of the learning environment enables interactivity with the system. (H12)	80% / 8% / 12%
12	High levels of interactivity of a learning environment correspond with a focus of attention on the activities in the learning environment. (H8)	86% / 0% / 24%
13	A clear set of learning goals corresponds to improved flow. (H14)	48% / 28% / 24%
14	A balanced skill and challenge ratio by the user and domain model of the system enhances the flow experience. (H17)	68% / 28% / 4%
15	Using selected still images rather than streaming video can increase learning if the auditory narration quality of the original video is maintained. (H2)	68% / 8% / 24%
16	The sequence of the multimedia mix (first text, then video versus first video, then text) affects learning. (H11)	44% / 16% / 40%
17	A clear increase of the resolution of videos and images leads to increase of learning. (H10)	20% / 36% / 44%

The 17 hypotheses use almost the full available range (1-10 or 11-17), while Standard Deviation (SD) stays between 2.45 and 3.09 for all hypotheses throughout all rounds.

Kendall's Tau coefficients as well as Spearman's Rho are high between round 1 and round 2, and even higher for rounds 2 and 3 (see Table 14). This strong positive correlation between rankings in the two final rounds as well as the high Tau values shows that the ranking is stable. Panel decisions, although diverse, did not change much between rounds, which indicates that three Delphi rounds were a sufficient number to find the maximum possible consensus [228] [110].

Table 14: Spearman's Rho and Kendall's Tau

	Spearman's Rho	**Kendall's Tau**
Round 1 and 2	0.797	0.69
Round 2 and 3	0.850	0.76

5.3.3 Results Delphi Study – Individual Hypotheses

In the following the results for the individual hypotheses will be presented in more detail, in the order of the final ranking from most to least important (see Table 13). The presented results document how the ranking of the hypotheses evolved as well as the changes of opinion of the experts. In particular for controversial hypotheses these changes are often reflected in changing levels of agreement.

H9: Better ease of use of the learning environment corresponds with clearer focus of attention. (See Table 15)

There were very few comments, pointing out that a system too easy to handle might actually not challenge the learners sufficiently.

There were no doubts about the hypothesis. Disagreement percentages went from weak disagreement to no disagreement and agreement percentages went from high agreement to highest agreement percentage over the course of the three rounds. The range interval decreased slightly, but the SD got slightly bigger. The wide range of ranks and the fairly high SD indicate disagreement among the panel within the rounds. The hypothesis was consistently ranked first.

Table 15: Agreement and Importance values for Hypothesis 9

		Round 1	Round 2	Round 3
Agreement	Strongly agree	n/a	70.4%	72.0%
	Agree	80.6%	29.6%	24.0%
	Partially agree / No opinion	16.1%	0.0%	4.0%
	Disagree	3.2%	0.0%	0.0%
	Strongly disagree	n/a	0.0%	0.0%
Ranking	Median	n/a	3	3
	Range	n/a	1-10	1-9
	Rank	n/a	1	1
	Mean	n/a	3.89	3.48
	SD	n/a	2.45	2.58
	Rank	1	1	1

H7: Ongoing system feedback about progress results in more intense learning. (See Table 16)

There were few comments. The comments confirmed the hypothesis, but pointed out the importance of choosing the right methods for communication. Doubts focused on the benefit of communication that might provide too much and too frequent feedback. Disagreement percentages went from very weak disagreement to no disagreement and eventually changed to strong agreement percentages. The range interval decreased slightly, as well as the SD. This indicates a tendency towards agreement within the rounds. The hypothesis ranking went from 6 in the first round to second in the final round. A majority of the panellists changed their opinion about the ranking between the second and third round.

Table 16: Agreement and Importance values for Hypothesis 7

		Round 1	**Round 2**	**Round 3**
Agreement	Strongly agree	n/a	33.3%	40.0%
	Agree	67.7%	55.6%	48.0%
	Partially agree / No opinion	29.0%	11.1%	12.0%
	Disagree	3.2%	0.0%	0.0%
	Strongly disagree	n/a	0.0%	0.0%
Ranking	Median	n/a	5	5
	Range	n/a	1-10	1-9
	Rank	n/a	4	2
	Mean	n/a	4.93	4.64
	SD	n/a	2.73	2.51
	Rank	6	3	2

H6: Providing a choice between a linear course structure and an open learning environment improves learning results. (See Table 17)

This hypothesis was controversial, producing a large number of comments and doubts. Most comments focused on the necessity for the learner to be able to switch between the two options and the impact learning style might have on the selection of one of the two options. Agreement percentages went from moderate to strong agreement percentages, with unusually high percentage of no opinion and weak disagreement percentages. The range interval decreased slightly, as well as the SD, indicating stronger agreement in the last round. This is reflected in the matching mean and median ranks in the last round. The hypothesis ranking went from 9 in the first round, 8 in the second to third in the final round.

Table 17: Agreement and Importance values for Hypothesis 6

		Round 1	**Round 2**	**Round 3**
Agreement	Strongly agree	n/a	29.6%	32.0%
	Agree	58.1%	55.6%	48.0%
	Partially agree / No opinion	38.7%	0.0%	12.0%
	Disagree	3.2%	14.8%	8.0%
	Strongly disagree	n/a	0.0%	0.0%
Ranking	Median	n/a	7	5
	Range	n/a	1-10	1-9
	Rank	n/a	10	3
	Mean	n/a	6.11	4.92
	SD	n/a	3.09	2.72
	Rank	9	8	3

H16: A more intense flow experience corresponds with improved learning results. (See Table 18)

There were only few comments, but most questioned that flow would have a positive impact on learning. Despite these doubts, agreement percentages were high and disagreement went from medium to weak. The range interval stayed the same while the SD decreased, again indicating stronger agreement, which is shown by the matching mean and median based ranking. The hypothesis ranking based on mean stayed the same between round one and three.

Table 18: Agreement and Importance values for Hypothesis 16

		Round 1	Round 2	Round 3
Agreement	Strongly agree	n/a	40.7%	44.0%
	Agree	77.4%	44.4%	40.0%
	Partially agree / No opinion	12.9%	3.7%	12.0%
	Disagree	9.7%	11.1%	4.0%
	Strongly disagree	n/a	0.0%	0.0%
Ranking	Median	n/a	7	5
	Range	n/a	1-10	1-10
	Rank	n/a	9	4
	Mean	n/a	6.04	5.28
	SD	n/a	3.03	2.53
	Rank	4	7	4

H3: Learning materials providing a mix of different media lead to improved learning results. (See Table 19)

Comments mostly regarded concerns about the quality of the mix and the learner's choice to select preferred media. There was some doubt whether a mix of media can actually cater for the needs of individual learners. Agreement percentages were consistently high and there was some disagreement only in the last round. The range interval stayed the same while the SD increased slightly, also reflected in the difference in mean and median based ranking. The hypothesis ranking based on mean overall stayed the same, but there was an outstanding 4-interval difference between mean and median rank in the last round.

Table 19: Agreement and Importance values for Hypothesis 3

		Round 1	**Round 2**	**Round 3**
Agreement	Strongly agree	n/a	40.7%	44.0%
	Agree	64.5%	44.4%	40.0%
	Partially agree / No opinion	35.5%	14.8%	8.0%
	Disagree	0.0%	0.0%	4.0%
	Strongly disagree	n/a	0.0%	4.0%
Ranking	Median	n/a	5	7
	Range	n/a	1-10	1-10
	Rank	n/a	2	9
	Mean	n/a	4.81	5.28
	SD	n/a	2.97	3.02
	Rank	5	2	5

H5: A clear set of learning goals outlined by the system corresponds to improved learning. (See Table 20)

Comments emphasize the need for the learner to define her own goal, combined with system goals. One suggestion was that the system and the learner should "negotiate" learning goals. There were some doubts whether goal setting would restrict inquiry-based and explorative learning. The number of comments shows a dramatic drop from round 1 to round 2. Some of the doubts mentioned challenge whether the concept of learning goals is sustainable for all learning theory approaches. Partial agreement shows a significant fall, while initially high agreement percentage increases slightly. Disagreement is on a low level and shows a light increase. The range shows a barely noticeable reduction. Median and mean based rank are very similar and show a small downward trend.

Table 20: Agreement and Importance values for Hypothesis 5

		Round 1	**Round 2**	**Round 3**
Agreement	Strongly agree	n/a	48.1%	44.0%
	Agree	61.3%	37.0%	40.0%
	Partially agree / No opinion	32.3%	3.7%	8.0%
	Disagree	6.5%	11.1%	8.0%
	Strongly disagree	n/a	0.0%	0.0%
Ranking	Median	n/a	6	6
	Range	n/a	1-10	2-10
	Rank	n/a	7	5
	Mean	n/a	5.56	5.52
	SD	n/a	3.12	3.14
	Rank	7	5	6

H15: Improvement of QoS when delivering various multimedia types can improve the flow experience. (See Table 21)

The few comments on this hypothesis pointed out that there is a threshold above which further QoS improvements will not make a difference and that QoS parameters depend on the type of media. No doubts were expressed. Agreement percentages were consistently high and the small percentage of disagreement disappeared by the last round. The percentage with no opinion got considerably smaller as well. The range interval stayed the same while the SD decreased slightly. The hypothesis ranking based on the mean varied strongly and there was an outstanding 4-interval difference between mean and median rank in the second and a 3-interval difference in the last round.

Table 21: Agreement and Importance values for Hypothesis 15

		Round 1	**Round 2**	**Round 3**
Agreement	Strongly agree	n/a	29.6%	16.0%
	Agree	74.2%	59.3%	76.0%
	Partially agree / No opinion	22.6%	11.1%	8.0%
	Disagree	3.2%	0.0%	0.0%
	Strongly disagree	n/a	0.0%	0.0%
Ranking	Median	n/a	6	6
	Range	n/a	2-10	2-10
	Rank	n/a	6	6
	Mean	n/a	6.37	5.84
	SD	n/a	2.59	2.43
	Rank	3	10	7

H13: Increased attractiveness of a learning environment enhances flow. (See Table 22)

Comments point out that attractiveness is highly subjective. Agreement is high and shows an upward trend, complemented by declining partial agreement percentage. Disagreement was very low. The range is moderate and does not change. The median rank showed an increase. Median and mean based ranks showed a significant difference in round 2, but were very similar in the final round.

Table 22: Agreement and Importance values for Hypothesis 13

		Round 1	**Round 2**	**Round 3**
Agreement	Strongly agree	n/a	22.2%	24.0%
	Agree	71.0%	59.3%	72.0%
	Partially agree / No opinion	29.0%	14.8%	4.0%
	Disagree	0.0%	3.7%	0.0%
	Strongly disagree	n/a	0.0%	0.0%
Ranking	Median	n/a	6	6
	Range	n/a	1-10	2-10
	Rank	n/a	5	7
	Mean	n/a	6.15	6.04
	SD	n/a	2.55	2.64
	Rank	2	9	8

H4: A balance of skill and challenge managed by the system corresponds with increased learning. (See Table 23)

The number of comments was moderate and they mainly enforced or confirmed the hypothesis. The overall agreement increased, while partial agreement showed a significant fall. Disagreement percentages, initially on a low level, disappeared completely. The range was moderate and stable. Mean and median based were very similar and showed a parallel trend towards a lower rank.

Table 23: Agreement and Importance values for Hypothesis 4

		Round 1	**Round 2**	**Round 3**
Agreement	Strongly agree	n/a	33.3%	32.0%
	Agree	58.1%	48.1%	64.0%
	Partially agree / No opinion	38.7%	11.1%	4.0%
	Disagree	3.2%	7.4%	0.0%
	Strongly disagree	n/a	0.0%	0.0%
Ranking	Median	n/a	5	6
	Range	n/a	1-10	1-10
	Rank	n/a	3	8
	Mean	n/a	5.26	6.32
	SD	n/a	2.65	2.85
	Rank	8	4	9

H1: Applying conversation style texts correspond with more intense learning for beginners. (See Table 24)

Comments point out that this hypothesis depends very much on context and the audience. Agreement percentage as well as partial agreement show a sharp fall, while disagreement displays a sharp increase. The range is moderate but moves from the low half of the ranks to the top half. Mean and median based ranks are the same.

Table 24: Agreement and Importance values for Hypothesis 1

		Round 1	**Round 2**	**Round 3**
Agreement	Strongly agree	n/a	11.1%	4.0%
	Agree	48.4%	70.4%	64.0%
	Partially agree / No opinion	48.4%	3.7%	8.0%
	Disagree	3.2%	14.8%	20.0%
	Strongly disagree	n/a	0.0%	4.0%
Ranking	Median	n/a	13	9
	Range	n/a	11-17	1-10
	Rank	n/a	12	10
	Mean	n/a	12.30	7.68
	SD	n/a	1.66	2.76
	Rank	11	12	10

H12: Ease of use of the learning environment enables interactivity with the system. (See Table 25)

A few participants expressed their understanding of the hypothesis while one participant questioned the hypothesis in general, but there were very few comments altogether. A fairly high initial partial agreement is given up in favour of agreement, which displays a steady increase, while the fairly high disagreement declines in parallel. The range is moderate and stays the same. The mean and median based rank are extraordinarily exact the same through the rounds.

Table 25: Agreement and Importance values for Hypothesis 12

		Round 1	**Round 2**	**Round 3**
Agreement	Strongly agree	n/a	29.6%	28.0%
	Agree	61.3%	48.1%	52.0%
	Partially agree / No opinion	22.6%	7.4%	8.0%
	Disagree	16.1%	11.1%	12.0%
	Strongly disagree	n/a	3.7%	0.0%
Ranking	Median	n/a	12	13
	Range	n/a	11-17	11-16
	Rank	n/a	11	11
	Mean	n/a	12.30	12.80
	SD	n/a	1.66	1.32
	Rank	12	11	11

H8: High levels of interactivity of a learning environment correspond with a focus of attention on the activities in the learning environment. (See Table 26)

The importance of finding the right balance between learning support through interaction and distraction is the focus of the majority of the moderate number of comments. The significant increase in disagreement is paralleled by a drop of the initially very high partial agreement. Moderate to strong agreement shows a slow increase. Median and mean based ranks converge from round 2 to round 3. The SD reflects this with a noticeable decrease.

Table 26: Agreement and Importance values for Hypothesis 8

		Round 1	**Round 2**	**Round 3**
Agreement	Strongly agree	n/a	37.0%	28.0%
	Agree	64.5%	44.4%	48.0%
	Partially agree / No opinion	25.8%	3.7%	0.0%
	Disagree	9.7%	14.8%	20.0%
	Strongly disagree	n/a	0.0%	4.0%
Ranking	Median	n/a	6	13
	Range	n/a	1-10	11-17
	Rank	n/a	8	12
	Mean	n/a	5.89	12.84
	SD	n/a	2.99	1.62
	Rank	10	6	12

H14: A clear set of learning goals corresponds to improved flow. (See Table 27)

The moderate numbers of comments reflect doubts about the hypothesis; in particular that flow experience and learning goals are conflicting concepts. Agreement percentage is moderate while partial agreement as well as disagreement percentages is high throughout. Median and mean based ranks are the same and vary only very little and the moderate range stays the same. This is one of the most stable results, reflected also in low SD values.

Table 27: Agreement and Importance values for Hypothesis 14

		Round 1	**Round 2**	**Round 3**
Agreement	Strongly agree	n/a	14.8%	20.0%
	Agree	48.4%	40.7%	28.0%
	Partially agree / No opinion	29.0%	22.2%	28.0%
	Disagree	22.6%	14.8%	20.0%
	Strongly disagree	n/a	7.4%	4.0%
Ranking	Median	n/a	13	13
	Range	n/a	11-17	11-17
	Rank	n/a	14	13
	Mean	n/a	13.70	13.00
	SD	n/a	2.03	1.93
	Rank	15	14	13

H17: A balanced skill and challenge ratio by the user and domain model of the system enhances the flow experience. (See Table 28)

The moderate number of comments reflects uncertainty about the hypothesis. This is reflected in the second highest percentage of partial agreement combined with a low agreement percentage and a declining disagreement percentage. Mean and median based ranks are the same and both vary only slightly. This is mirrored in a low SD and a consistently moderate range.

Table 28: Agreement and Importance values for Hypothesis 17

		Round 1	**Round 2**	**Round 3**
Agreement	Strongly agree	n/a	18.5%	12.0%
	Agree	51.6%	51.9%	56.0%
	Partially agree / No opinion	35.5%	18.5%	28.0%
	Disagree	12.9%	11.1%	4.0%
	Strongly disagree	n/a	0.0%	0.0%
Ranking	Median	n/a	13	13
	Range	n/a	11-17	11-16
	Rank	n/a	13	14
	Mean	n/a	13.67	13.20
	SD	n/a	1.73	1.26
	Rank	13	13	14

H2: Using selected still images rather than streaming video can increase learning if the auditory narration quality of the original video is maintained.
(See Table 29)

There was a variety of comments. It was accentuated that the validity of the statement depends on the quality of the selected images and the context of the video or images. Certain content is more suitable than other for either video or images. One key point was that still images might focus the learner's concentration. Some input also pointed out that streaming images support subliminal learning. There were a few doubts that images rather than video would actually increase learning. Agreement percentages more or less stayed moderate, but percentage for disagreement increased clearly, including some strong disagreement in the final round. The range interval stayed the same and SD increased slightly. The ranking went down by one from the first to the second round and stayed the same in the two final rounds.

Table 29: Agreement and Importance values for Hypothesis 2

		Round 1	Round 2	Round 3
Agreement	Strongly agree	n/a	7.4%	4.0%
	Agree	35.5%	51.9%	64.0%
	Partially agree / No opinion	54.8%	18.5%	8.0%
	Disagree	9.7%	22.2%	20.0%
	Strongly disagree	n/a	0.0%	4.0%
Ranking	Median	n/a	15	15
	Range	n/a	11-17	11-17
	Rank	n/a	15	15
	Mean	n/a	14.37	14.88
	SD	n/a	1.78	1.81
	Rank	14	15	15

H11: The sequence of the multimedia mix (first text, then video versus first video, then text) affects learning. (See Table 30)

There were a moderate number of comments, pointing out that the validity of this hypothesis depends very much on the content and its quality. Doubts focused on the lack of consideration of this topic in previous research and recommended more studies to investigate this hypothesis. Percentages went from moderate agreement and moderate disagreement to equally strong agreement and disagreement. The initially undecided mostly changed their minds towards disagreement. The range interval as well as SD was stable. This indicates a tendency towards agreement within the rounds. The hypothesis was consistently ranked second last.

Table 30: Agreement and Importance values for Hypothesis 11

		Round 1	**Round 2**	**Round 3**
Agreement	Strongly agree	n/a	7.4%	4.0%
	Agree	45.2%	25.9%	40.0%
	Partially agree / No opinion	32.3%	37.0%	16.0%
	Disagree	22.6%	25.9%	40.0%
	Strongly disagree	n/a	3.7%	0.0%
Ranking	Median	n/a	15	16
	Range	n/a	11-17	11-17
	Rank	n/a	16	16
	Mean	n/a	14.89	15.12
	SD	n/a	1.6	1.86
	Rank	16	16	16

H10: A clear increase of the resolution of videos and images leads to increase of learning. (See Table 31)

The comments pointed out that an increase of resolution has to start at a very low level of resolution to be noticeable. Doubts focused on the importance of the topic for an impact on learning. Agreement percentages went down consistently and percentage for disagreement equally increased, although "strong disagreement" was not selected. The range interval got considerably smaller as well as SD. The ranking consistently stayed the same; it was the lowest rank throughout.

Table 31: Agreement and Importance values for Hypothesis 10

		Round 1	**Round 2**	**Round 3**
Agreement	Strongly agree	n/a	11.1%	0.0%
	Agree	22.6%	7.4%	20.0%
	Partially agree / No opinion	51.6%	29.6%	36.0%
	Disagree	25.8%	51.9%	44.0%
	Strongly disagree	n/a	0.0%	0.0%
Ranking	Median	n/a	16	17
	Range	n/a	11-17	13-17
	Rank	n/a	17	17
	Mean	n/a	15.48	16.12
	SD	n/a	1.78	1.2
	Rank	17	17	17

5.4 Analysis and Discussion

The analysis of the Delphi results consists of two parts. First, a general analysis of Delphi results examines consensus, stability, and ranking. Then the results are analysed in terms of the initial categories from the literature review - learning, flow experience, user experience and Quality of Service. All hypotheses were initially given to an advisor panel consisting of experts from the respective research areas, to ensure that the hypotheses are relevant and unambiguous (see 5.3.1).

5.4.1 General Analysis

Consensus on the ranking of a hypothesis is reflected in the range and the standard deviation (SD) - a small range in combination with a low SD value indicates higher consensus on the ranking. SD shows the strength of aggregate judgement, while larger range indicates the presence of outlier views. The consensus is reflected in the comparison of the mean-based and the median-based ranking. If the values are equal it indicates that the ranking of the hypothesis is stable, while divergence indicates a weaker ranking decision.

The progression of disagreement and agreement shows the consensus among the panel about the acceptance of the hypothesis itself; the smaller the range of these values, the stronger the consensus about the hypothesis. This is complemented by the type of agreement and the number of comments. High and consistent values for agreement indicate that the hypothesis is accepted, while high values for disagreement point in the opposite direction. If the number of comments is high this indicates a more controversial hypothesis and vice versa. The number of comments is expected to get significantly lower from one round to the next; otherwise it indicates controversy about the hypothesis [109].

An overview of the results for the convergence of ranking (see Figure 37) shows that the ranking of approximately half of the hypotheses varies considerably, while the other half is fairly stable or does not change at all. It stands out that extreme ranks are very stable. The hypotheses ranked first, last and second last do not show any variation of the ranking throughout the rounds. The consensus on these ranks is very strong. The hypotheses with middle ranks in the final round show a wide range across rounds (see Figure 37), indicating ambivalence about their importance ranking.

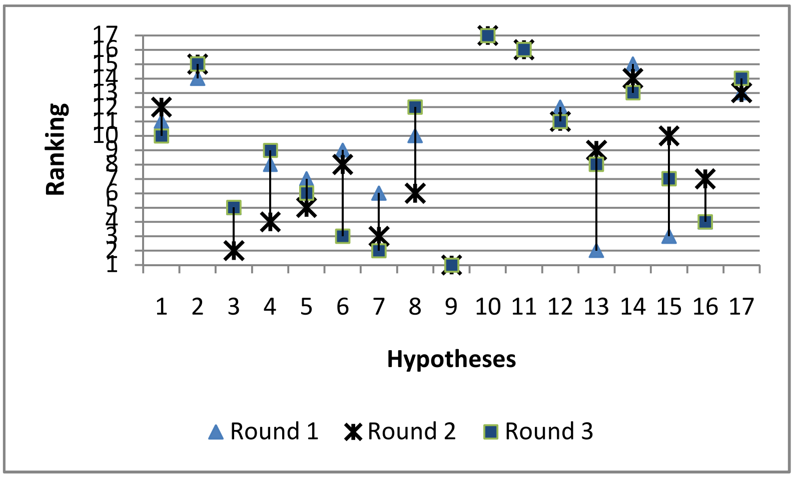

Figure 37: Hypotheses Ranking Rounds 1 to 3

Hypotheses were ranked by the panel across the whole range of available ranks; e.g. the hypothesis finally ranked third also got ranked ninth and eighth. This spread of rankings can also be seen in the difference of mean and median ranks. It is more likely for mean and median rank to vary, if the range of the rankings is spread out. SD can be considered stable for all hypotheses except hypothesis 16, where it decreases significantly.

The percentage agreement (see Figure 38) demonstrates the evolution of consensus. The percentage agreement went up for most hypotheses from round 1 to 3, with the exception of hypotheses 10, 11 and 14. The agreement levels are also very consistent for most hypotheses, except for the three mentioned previously. This is a first indication that the panellists' decisions were stable throughout the rounds. Agreement levels below 70% in the first round characterize the hypotheses ranked between thirteen and seventeen in the final round. On the other hand consistent agreement levels above 80% across all three rounds do not necessarily indicate a high ranking in the final round. E.g. hypotheses 13 and 15 with agreement levels above 80% have final ranks seven and eight.

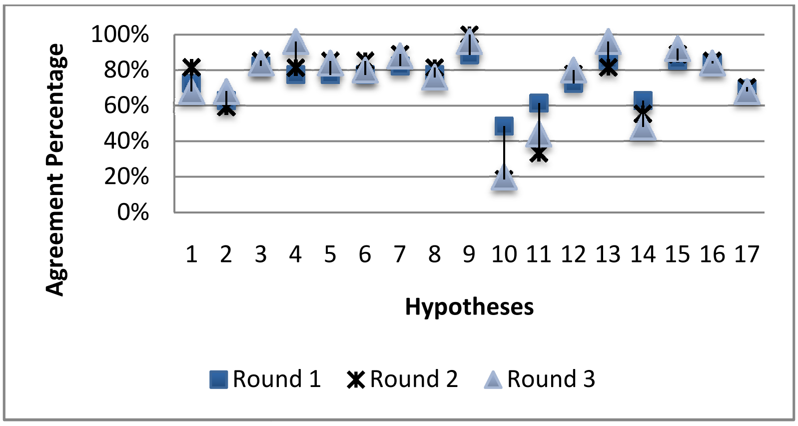

Figure 38: Percentage of agreement rounds 1 to 3

The disagreement percentage went down for most hypotheses from round one to round three (see Figure 39), except for hypotheses 1, 8 and 11. Hypotheses with an increase in disagreement are all finally ranked between 11 and 17. Hypotheses with a disagreement level below 20% in the first round have a final ranking among the first eight ranks. The hypothesis ranked 1-5 all exhibit final disagreement levels below 10%. The hypotheses with no disagreement in the final round are all in the top half of the ranks.

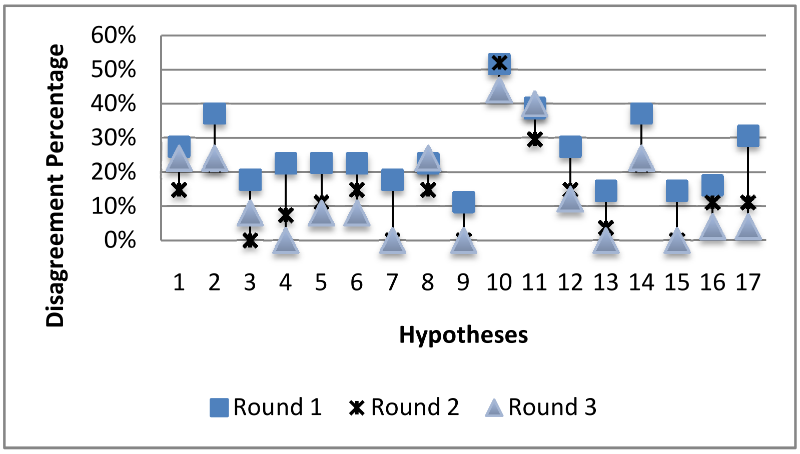

Figure 39: Percentage Disagreement Rounds 1 to 3

The evolution of consensus can also be seen in the number of comments (see Figure 40). Generally the number of comments decreased significantly for all hypotheses between round 1 and 2. Most comments in the last round are reinforcement of the hypotheses rather than actual comments. The general decrease in comments indicates a strong overall consensus in the final round (see Figure 40).

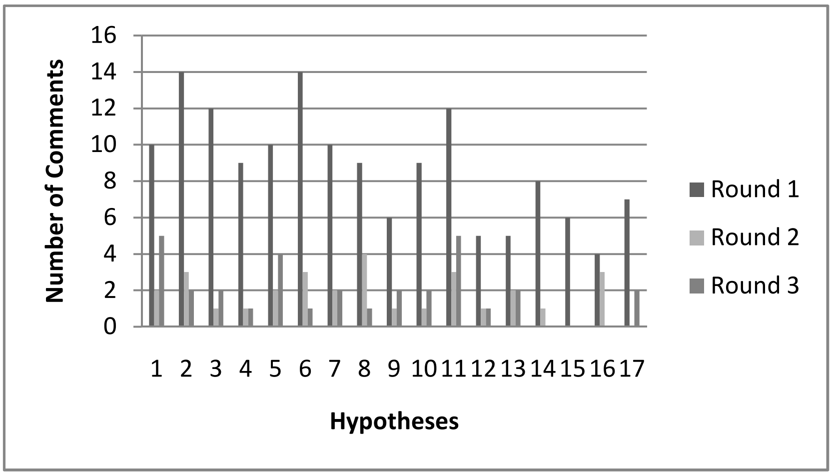

Figure 40: Comments per Round

In summary it can be said that a low initial agreement level was correlated with a low final ranking, while disagreement level below 20% in the first round characterizes hypotheses in the top half of the ranks. Highly ranked hypotheses show high agreement and low disagreement levels. This means that hypotheses participants agreed with also received good importance ranking.

The wide range of ranks selected for each hypothesis over the course of the three rounds in combination with different mean based ranks across rounds indicates a strong ambivalence of the results. It can be argued that this is due to the ambiguity of most areas involved. The concept of learning is still widely debated and there is no final agreement among experts beyond this study what makes learning successful. The psychological concept of flow experience has been investigated very diversely. The impact of Quality of Service on learning is a very young research area. In summary the heterogeneity of the results reflects this diversity and ambiguity.

5.4.2 Analysis of Hypothesis Categories

The analysis of results relating to individual hypotheses can be summarized with an analysis of categories of the hypotheses (see Figure 41). Hypotheses are divided by their main focus into the following four categories: QoS, learning, flow experience and user experience. In the following, we consider not only the final ranking of hypotheses, but the degree of agreement achieved.

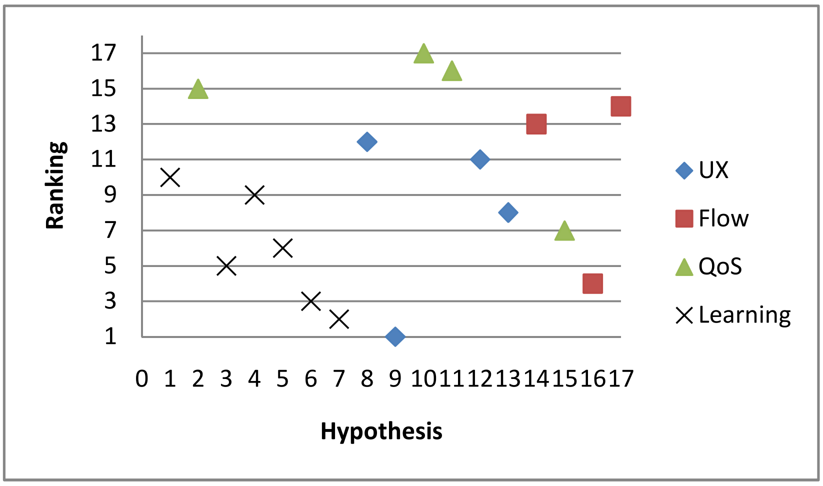

Figure 41: Category Rankings

Category Ranking

Learning-related hypotheses are all among the first ten ranks. The hypothesis with the lowest rank in this category also has the lowest agreement level, as well as the highest disagreement level. This indicates high relevance for this category. User-experience-related hypotheses have medium ranks between eight and twelve, except for hypothesis nine, which consistently was ranked first. This means this category is relevant, but does not have the same priority as the learning-related hypotheses. Flow-related hypotheses show low ranks except for hypothesis 16, which is ranked fourth, indicating low relevance. Finally QoS-related hypotheses are considered not very relevant in comparison with the other categories, considering their consistently extremely low ranking. One interpretation of these results is that the more established areas such as learning and user experience were ranked higher than the areas less established. However, it should be noted that there is a mix of learning, flow and usability-related hypotheses among the first five.

Category Agreement and Stability

While the ranking of hypotheses is extremely important, it is useful to consider this ranking in the context of the degree of agreement achieved. Many hypotheses achieved a good degree of consensus, but for others, there was much controversy and in the end the experts "agreed to disagree". In the following we analyse the consensus and ranking trends for the top five ranked hypotheses. Hypotheses were ranked by the panel across the whole range of available ranks; e.g. the hypothesis finally ranked first also got ranked ninth three times. This spread of rankings can also be seen in the difference of mean and median ranks. It is more likely for mean and median rank to vary, the more the rankings are spread out. SD can be considered stable for all hypotheses except hypothesis 16, where it decreases significantly.

Hypothesis nine, ranked 1st consistently, shows stable and very high agreement levels with no disagreement in the last round. The number of comments started with one of the lowest number of comments went down significantly, although there was a slight increase in the last round. Mean and median based ranking are the same. In conclusion the ranking of hypothesis nine can be considered very stable.

Hypothesis seven, ranked second in the last round, initially has a much lower ranking, but moves up in the second round and continues the upward trend in the final round. Agreement levels are almost identical and at a very high percentage, while disagreement percentage starts with a moderate percentage and closes with no disagreement in the final round. The number of comments drop between the first and second rounds and then stays on that low level. Mean and median based ranking vary in the second round, but stabilize and are the same in the last round. The ranking of the hypothesis can therefore be considered moderately stable.

Hypothesis six, ranked third in the last round, shows similar results as hypothesis seven. It does start with the highest number of comments and consistently drops to the lowest level in the final round. Therefore the ranking can also be considered moderately stable.

Hypothesis sixteen, ranked fourth in the final round, also started out with this ranking in the first round. Agreement is almost the same on a very high level throughout rounds, while disagreement level continuously drops to a finally low level close to zero. The number of comments starts low and there are no comments in the final round. The mean and median based ranking varies in round two, but is the same for the final round and the SD drops, which makes it also moderately stable.

Summary of Category Discussion

The analysis of the rankings and categories of hypotheses shows that learning-related hypotheses are on average ranked much higher than flow-related hypotheses and even higher than QoS-related hypotheses. This corresponds with an initial model for Learner Quality of Experience [157] which considers learning and flow to directly affect QoE, while QoS impacts QoE indirectly via the aforementioned factors. The strong values for the ranking rounds in combination with the high levels of agreement of the hypotheses ranked first to fifth rank allow the conclusion that these, namely, ease of use of the learning environment, ongoing system feedback, a choice between a guided and an open learning environment and learning materials providing a mix of media are requirements for good QoE in adaptive multimedia e-learning systems. Hypotheses continuously ranked between 11 and 17 show mixed levels of agreement/disagreement. Most outstanding among those are the continuously low ranks of QoS-related hypotheses. This indicates need for further research in particular on the QoS-related hypotheses to find more detailed information on their impact on QoE.

5.4.3 Conclusions

The aim of the Delphi study was to identify aspects relevant for QoE by investigating agreement levels and ranking of a list of 17 hypotheses, relating to learning, QoS, flow experience and user experience. The hypotheses were initially drawn from a literature review, followed by a round of expert interviews with an advisor panel. These interviews had the goal to discuss the validity, relevance and ambiguity of the chosen hypotheses. The hypotheses were given to a heterogeneous expert panel on Learner Quality of Experience in adaptive QoS-aware multimedia e-learning systems. The range of experts involved in the interviews and the Delphi study and their research areas represent the complexity of the concept of Quality of Experience. The wide range of ranks selected for each hypothesis indicates an ambivalence of the results. It can be argued that this ambivalence exists due to the ambiguity of most areas involved. The concept of learning, although discussed for centuries, is still widely debated and there is no final conclusion among experts beyond this study what makes learning successful. The concept of flow has been investigated very diversely in the recent past and the impact of Quality of Service on learning is a very young research area. In conclusion this means that the heterogeneity of the results reflect this diversity and ambiguity. Nevertheless the analysis of the rankings and categories of hypotheses shows that learning-related hypotheses are on average ranked much higher than flow-related hypotheses. QoS-related hypotheses tended to be ranked very low. This corresponds with the initial model for Learner Quality of Experience (Figure 31) which considers indirect QoS-impact on QoE by affecting learning and flow.

In a final synthesis the strong values for the ranking rounds in combination with the high levels of agreement of the hypotheses ranked first to fifth rank allow the conclusion that these hypotheses describe requirements for adaptive multimedia e-learning systems. Likewise the strong results for the rankings in combination with the mixed levels of agreement and disagreement for the hypotheses ranked between 11 and 17 allow the conclusion that these hypotheses are most controversially discussed. The study shows that flow experience and learning could be confirmed as aspects relevant to QoE, while the impact of QoS needs further investigation to find more detailed information on the impact of QoS on the QoE of the learner. To strengthen the case of the impact of QoS in multimedia e-learning it is necessary to find proof that there is some coherence. QoS and its impact have been investigated in a very direct way, looking for a strong immediate impact on e-learning, but did not make a good case. The reluctance of the Delphi panel possibly reflects this. Further work therefore includes simulations of an algorithm considering these findings and looking for objective measures representing indirect impact and user tests to evaluate the results in real life scenarios; the simulations are described in chapter 6, user tests are described in chapter 7.

6 Simulation-based Test Results and Analysis

6.1 Introduction

We propose to enhance QoE for adaptive e-learning through an adaptation that combines Quality of Service (QoS) information with a media mix strategy and the psychological concept of the flow. The Delphi study presented in the previous chapter showed that flow experience is considered a relevant aspect by the experts, however most flow-related hypotheses were ranked low. QoS-related hypotheses on the other hand were continuously ranked very low and received very low agreement. This shows that in particular the impact of flow experience and QoS on the QoE of the learner needs further investigation. Flow experience can be evaluated with subjective testing involving the target user or learner group, but not with simulations and will therefore be explored further in the next chapter of this thesis.

Simulations can show whether QoS adaptation strategies improve objective measures, such as startup delay and network usage, which will both affect flow experience and learning. The simulations analyse system behaviour when multimedia e-learning sessions are performed in an environment with changing network conditions. Figure 42 summarizes typical e-learning scenarios, with an e-learning server delivering various media types over the internet to learners with different internet connections (dial-up, DSL 2, DSL3).

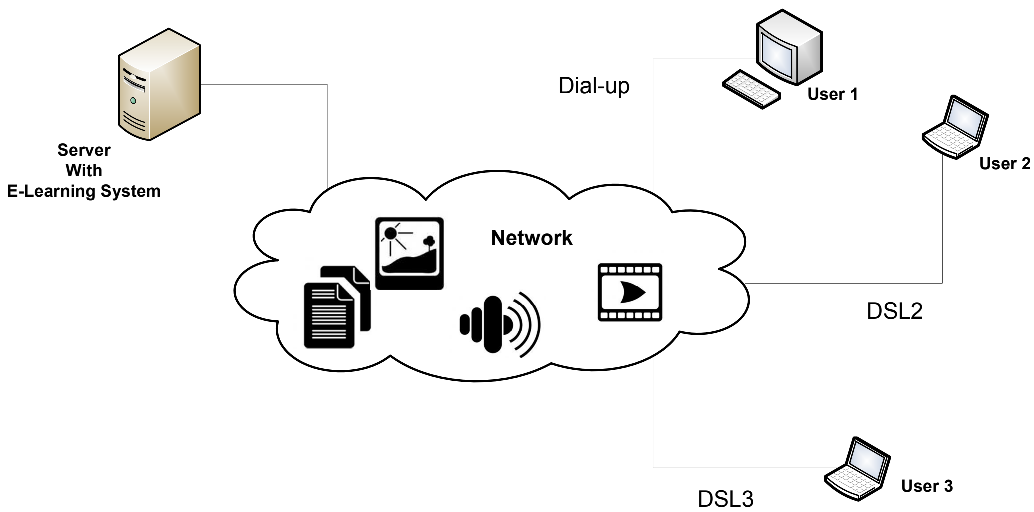

Figure 42: General Multimedia E-Learning Scenario

The simulations have two main goals:

- Investigate the impact on performance if only QoS-adaptivity is applied (QAMM1)
- Investigate the impact on performance if the combined QoS and media mix adaptivity is applied (QAMM2)

The results show that adaptation to the combination of available bandwidth and media mix provides a media mix similar to e-learning design, while causing much shorter start-up delays.

6.2 Simulation Setup

6.2.1 Media Profiles

For the purpose of comparison I considered two types of profiles of media mix for the simulations, Fixed Media Mix (FMM) and Quality-Adaptation for Media Mix (QAMM). The adaptation profiles vary in the number of constraints; QAMM1 only adapts to available bandwidth, while QAMM2 maintains a media mix in addition to that.

The media mix differs in the percentage of text, audio and video. FMM profiles have a predetermined composition (see Table 32).

The QAMM profiles follow the proposed adaptation policies and consequently vary in their media distribution depending on network conditions and media history. Profile 1 (QAMM1) provides adaptation to network conditions without consideration of the media mix. QAMM Profile 2 (QAMM2) considers network conditions as well as media history and aims to avoid repeating the same media. The QAMM media distributions will be presented with the results.

For the FMM profiles the simulation uses a media mix aiming to represent the instructional design of a multimedia e-learning course. Research results on media-richness in e-learning [206] [141] were discussed with e-learning authors to identify a typical media mix in e-learning. The two FMM profiles vary in their composition of different media (see Table 32) and will not adapt to network conditions. Consequentially this defines their demands on bandwidth.

Table 32: Media Distribution of FMM Profiles

	Text + images	Audio + images	Video	Demands on Bandwidth
FMM Profile 1	80%	10%	10%	Low
FMM Profile 2	40%	30%	30%	Medium

There is a considerable difference between stored media and live media streaming [221]. The simulations were based on streaming stored media, since live streaming is not very common in e-learning. Audio files and videos can be described by characteristics of streaming media (see Table 33) [138] [221].

Table 33: Characteristics of Streaming Media on the Web [221]

	Audio	Video	Internet Connection
Median duration	2 minutes	4 minutes	--
Median encoded bit rate, kbps	28 kbps	200 kbps	--
Percentage encoded / bit rate	~90% 28-56kbps	29% 56 kbps	Modem
	~10% > 56kbps	~70% 56-768 kbps	Broadband
		~ 1% 768 – 1500 kbps	T1
		< 1% 1540kbps	Above T1

The table shows that a larger percentage of streaming video targets lower bitrates, because improved streaming technology enables to efficiently send streams at lower bitrates [221]. Good performance can be expected if the available network bandwidth is roughly twice the media bit rate, with a few seconds of startup delay on the client's side. The wired connection is duplex, so upload of ack does not affect the available bandwidth for download. Most broadband connections support download rates of 750 Kbps - 1 Mbps [221].

6.2.2 Metrics

The performance was assessed, measuring average startup delay and the efficiency of the network usage. Startup delay is used as quality metric instead of an objective multimedia quality metric such as Peak Signal to Noise Ratio (PSNR) [222]. PSNR would not provide much information, due to its fine-granular differentiation, while startup delay of the media affects the user experience [101] and therefore appears to be more suitable.

Network usage is considered in terms of resource efficiency based on total bandwidth of the bottleneck connection. Periods of peak usage of network resources are expensive to a provider, while a stable use of the network is manageable much better. Maintaining a stable network usage, as high as necessary to deliver sufficient material, with as small a startup delay as possible and an experience as varied as possible without creating peaks for usage of network resources is the goal of the adaptation.

6.2.3 Network simulator

The simulations were performed using the Network simulator version 2 (NS-2) [164]. NS-2 is a discrete event-driven network simulator which reaches from network layers to application layer. It provides many network technologies including wired networking to wireless connectivity such as WLAN, etc. The main user interfacing tool is Tcl/Tk and the NS-2 application operates as a TCL interpreter. Objects are written in either C++ or OTcl, an object-oriented extension of Tcl. OTcl is used for configuration and setup, while C++ is used for detailed implementation.

6.3 Traffic and Network Model

Common e-learning scenarios are characterized by a mix of different types of media. Research on media-richness in e-learning [23] [141] shows that a combination of the three media types, illustrated text, illustrated audio and video, are commonly used. This was recently confirmed with e-learning authors in interviews on strategies in adaptive e-learning [190]. The media profiles in the first subsection describe the different combinations used for the simulations.

Elearn Traf caters for those demands concerning learning content which are based in the technical learner environment. The simulation aims to model the situation in a multimedia e-learning scenario described above, combined with typical internet connection profiles [111]. The simulations apply the dumbbell topology, which is a representation of the real life e-learning situation. The main characteristics are three different types of bandwidth areas; the bandwidth between the server and the internet connection (BW1), the bandwidth of the internet connection (BW2) and the bandwidth between the internet connection and the client (BW3). The traffic model and the network model are described in the second subsection.

Three commonly used types of internet connections which are used for the simulations and are outlined in the final subsection.

6.3.1 The Traffic Model

A simulation model for a multimedia application in NS-2 was built which can run over an http connection and uses the WWW traffic model. It simulates the behaviour of a multimedia e-learning application that includes a mix of media, avoiding immediate repeats of the same media as outlined previously.

The model was developed based on the SURGE technique [7] and adapted to the multimedia e-learning scenario. SURGE is a highly parameterisable tool. The goal of SURGE is to imitate web traffic HTTP requests from a fixed population of web users. We assume that this is very similar to the situation of an e-learning provider. Its distribution model considers in particular file sizes, embedded references and so-called active OFF time, the processing time that is spent by the browser for parsing files and preparing to start a new TCP connection.

Many traffic models in NS-2 are provided on the application layer. This includes statistical distribution models such as Poisson and specific application-based models such as the so-called web traffic model (WebTraf).

WebTraf is an application-based traffic generation model characterized by user equivalents and distribution models and is based on the SURGE model [7], [62]. In previous work related to QoE in e-learning [161] the NSWEB extension for NS-2 [166] has been used. NSWEB extension has not been updated and is therefore not available for the current default NS-2 version. In addition, NSWEB also only considers one type of media at a time. So rather than extending an outdated version of NSWEB NS-2 WebTraf model has been extended, which is based on the SURGE technique as described above. The SURGE model is adopted to represent a web page with text and images. SURGE considers several embedded objects of the same media type in a page and the Pareto-II distribution reflects the number of embedded objects in a page, while we have one embedded object which can vary in size dramatically. Consequently, WebTraf has the same limitations as SURGE, such as supporting one media type only in a web page. However, the model presents good characteristics of web access. In addition we consider video and audio distribution models for stored-media streaming presented in [221], which capture general characteristics of web audio and video data.

The e-learning model for the simulation (ElearnTraf) is based on the WebTraf model, but modified to support different types of media such as text with images, audio and video and in our simulation only stored-media streaming is considered. The model describes the file size in a Pareto distribution, based on findings of [7], regarding text-based files and on findings of [138] for audio and video (see Table 34).

Table 34: Parameters of the SURGE model for video and audio [7]

	NS-2 distribution model	Parameters
Text with images	RandomVariable/Pareto	avg_ 133, shape_ 1.1
Audio	RandomVariable/Empirical	-
Video	RandomVariable/Empirical	-

Similar to WebTraf, ElearnTraf requires several distributions for the SURGE model. Each session has Inter Page time, Page Size and Inter Object parameters as described in Table 35. Inter-Page time is the time between the end of the previous page download and the start of the following page by the same user. Inter-object time is the time between requests to inlined objects of a web page. The page size describes the size of the page with all inlined objects.

Table 35: Values or parameters for Elearn Traf

	Parameter types	Values or parameters
Inter-Page time	RandomVariable/Pareto	avg_ 1, shape_ 1.5
Page Size	RandomVariable/Constant	1
Inter Object	RandomVariable/Exponential	avg_ 0.01

The media mix in ElearnTraf is defined by these characteristics.

To decide whether constant bit rate (CBR) or variable bit rate (VBR) is representative, measurement studies show that most videos streamed over the internet are CBR [138]. For simplicity reasons, it was assumed that audio and video are encoded with a constant bit rate and all packets are assumed to have the same size. The video length in Wang's research [221] is 80 seconds. The average video in a number of e-learning courses found online are between 60 - 180 seconds [206]. The simulations in NS-2 show that in stored-media streaming it is sufficient to model a relatively short video. Based on [138] we take the median of 3 minutes for video and audio clips as the duration of the clips.

6.3.2 The Network Model

A dumbbell topology is used for the simulation as shown in Figure 43. The network is characterized by three different bandwidth areas. Bandwidth 1 (BW1) between the sender (S) and the main network has a constant value. Bandwidth 2 (BW2) and Bandwidth 3 (BW3) vary, depending on the type of internet connection.

BW 1 is characterized by a very generous amount of available bandwidth, because this part of the connection will only be affected by limits of bandwidth if a large number of users request the same resource at the same time. This usually does not happen. BW2 has different values for the available bandwidth, depending on the type of internet connection and resembles the bottleneck in the connection. DSL 2 has the lowest available bandwidth, because several users share one connection and limit each others available bandwidth. BW2 is generous for the dial-up connection, because of the dial-up no competing traffic has to be considered. DSL 3 is similar to the dial-up not affected too much by competing traffic. Here the bandwidth provided is so large that there is very little limitation through competing traffic. BW 3 varies depending on the type of internet connection.

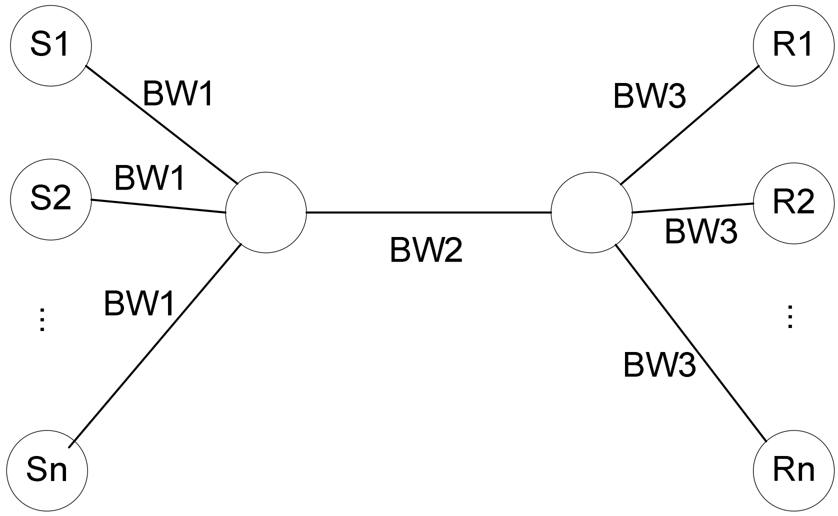

Figure 43: A typical dumbbell topology

The detailed configurations of topologies are summarized in Table 36.

Table 36: Configuration of topologies

	BW1	BW2	BW3
Dialup	10 Mbps	2 Mbps	56 kbps
DSL2	10 Mbps	700 kbps	10 Mbps
DSL3	10 Mbps	2 Mbps	10 Mbps

Using different topologies, each test is performed against the two approaches, QAMM and FMM. All the sessions in each test start at the same time at 0.1 seconds until 10 pages are transmitted successfully. The simulation considers multiple client-server connections. The number of sessions depends on the type of connection between client and server (see Table 37).

Table 37: Number of sessions for different types of connections

	Dialup	DSL 2	DSL 3
No. of Sessions	10	15	30

The dial-up connection reaches the maximum with 10 simultaneous sessions, while DSL 2 can handle 15 sessions and DSL 3 can handle 30 sessions. The maximum describes the point were due to limited bandwidth the mix of media does not change any further.

The simulations were run for the three configurations dialup, DSL2 and DSL 3.

The dialup configuration is set with BW1 at 10Mbps, BW2 at 2 Mbps and BW3, the direct connection to the receiver, is a bottleneck connection at 56kbps.

The DSL2 configuration is set and DSL3 both have a bottleneck connection in the middle (BW2) in order to represent the sharing of DSL services with several learners. BW2 has bandwidth of 700 kbps for DSL2 and 2 Mbps for DSL3. BW3 is set at 10 Mbps for both DSL connections.

The reduction of BW2 to 700 kbps for DSL2 simulates the reduced bandwidth due to the connection being shared. The same applies to the DSL3 connection; 2 Mbps for BW2 take into consideration that the much higher bandwidth is shared with many other users.

Simulating the dial-up scenario each session was set to a total number of 10 pages. Sessions simulating DSL2 and DSL3 connections were set to a total number of 15 and 30 pages respectively.

6.3.3 Simulation Scenarios

The following section describes the three scenarios used for the simulations. The simulations allow comparison of the impact of the algorithm for different network conditions. All scenarios include the traffic and network model, the FMM and QAMM media profiles and the adaptation algorithm described previously. They vary in topology and number of sessions.

Scenario 1: Dialup configuration

The dialup scenario simulates a sequence of request for web pages of a learner accessing a multimedia e-learning course with a dialup internet connection. The dialup configuration uses a 10 Mbps connection between server and network, a 2 Mbps connection for the main network and a 56 kbps connection from the network to the web client. The simulation runs until the maximum number of 10 sessions is reached with 10 pages per session. The bottleneck is the connection between the main network and the web client.

Scenario 2: DSL 2

The scenario simulates again a sequence of request for web pages of a learner accessing a multimedia e-learning course. This time the learner uses a DSL2 internet connection. In this scenario the bottleneck is the main network. It has a significantly reduced available bandwidth for the individual user, because it is shared with many users. The link between server and main network remains the same at 10 Mbps and the connection between main network and web client is increased to 10 Mbps. The connection between the main network and the web client is set fairly high to simulate that this link does not limit the available bandwidth once it has passed the main network. The simulation runs until the maximum number of 15 sessions is reached with 10 pages per session.

Scenario 3: DSL 3 connection

The DSL3 scenario varies to DSL2 in the size of the main network link and the number of sessions. The main network link is increased to 2 Mbps to consider the significantly increased available bandwidth of this similarly shared connection. The simulation runs until the maximum number of 15 sessions is reached with 10 pages per session.

6.4 The results

These three issues, startup delay, network usage and media mix will be discussed in the following text.

6.4.1 Average Startup delay

The adaptation algorithm reduces the average startup delays for all three configurations for both adapted profiles significantly (see Figure 44, Figure 45 and Figure 46). Table 38 summarizes the average startup delays of the four media mix profiles for all three configurations. It also presents the increase in startup delay (presented as percentage) when comparing all other profiles to QAMM 2.

Table 38: Comparison Average Startup delays

Average Startup delays							
Configuration	Dialup		DSL 2		DSL 3		AVG Increase
	time/s	Increase	time/s	Increase	time/s	Increase	
QAMM2	39.3	-	20.3		17.3		
FMM1	77.2	+96%	38.8	+91%	21.5	+24%	+70%
FMM2	172.0	+337%	115.2	+467%	69.6	+302%	+369%
QAMM1	59.2	+50%	44.0	+116%	41.7	+141%	+102%

As expected, average startup delays are highest for dialup configuration and lowest for DSL 3 configuration.

FMM1 has the smallest demands on bandwidth and could be expected to have the lowest values for average startup delay. But in fact QAMM 2, applying both aspects of the adaptation, shows even lower values for average startup delays for all three configurations. FMM1 has an average startup delay 96% higher than QAMM2 for the dialup connection. It is notable that even under excellent conditions of the DSL 3 configuration FMM1 shows a 24% increase of startup delay compared to QAMM2. However for low total number of sessions (<9) in the dialup connection FMM1 performs better than QAMM2 (see Figure 44).

FMM2 shows the highest startup delay across all configurations. Only for low number of sessions (<9) in the DSL3 configuration it performs better than QAMM1 (see Figure 46).

Furthermore it is remarkable that QAMM1, the profile that adapts to the network conditions, shows growing increases from dialup (+50%) to DSL 3 configuration (+141%) compared to QAMM2. This can be explained by the fact that QAMM2 also adapts to the media mix, which means that it will not always provide materials with high bandwidth demands, e.g. video when the network conditions allow. This impacts the resulting media mix comparison for the two adapted profiles, which will be presented further down.

In conclusion, QAMM2 clearly shows the lowest startup delay for all configurations.

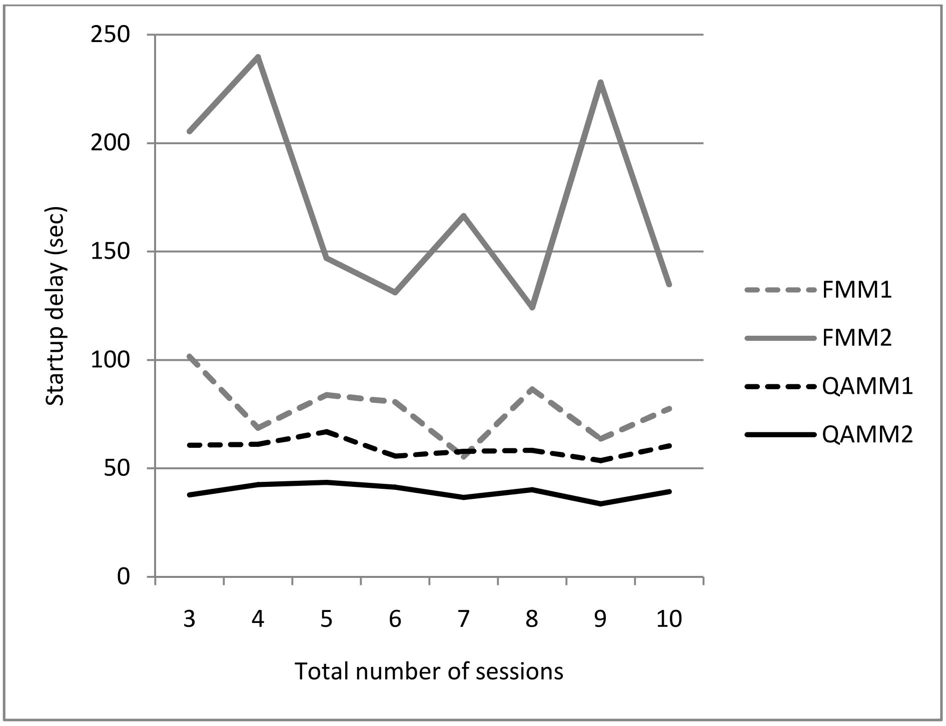

Figure 44: Average startup delay with dialup configuration

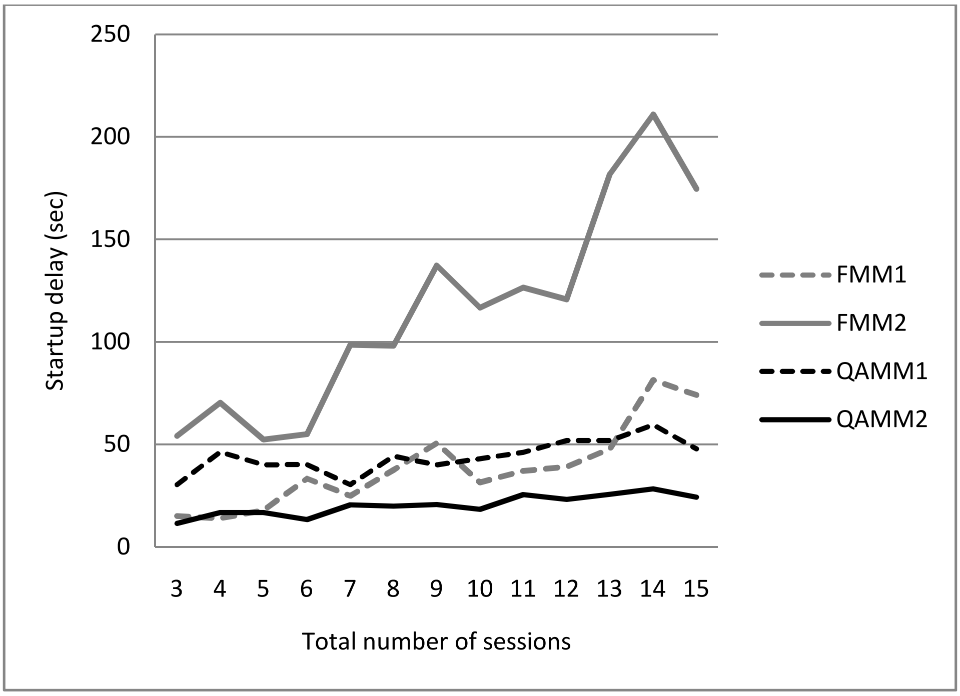

Figure 45: Average startup delay with DSL2 configuration

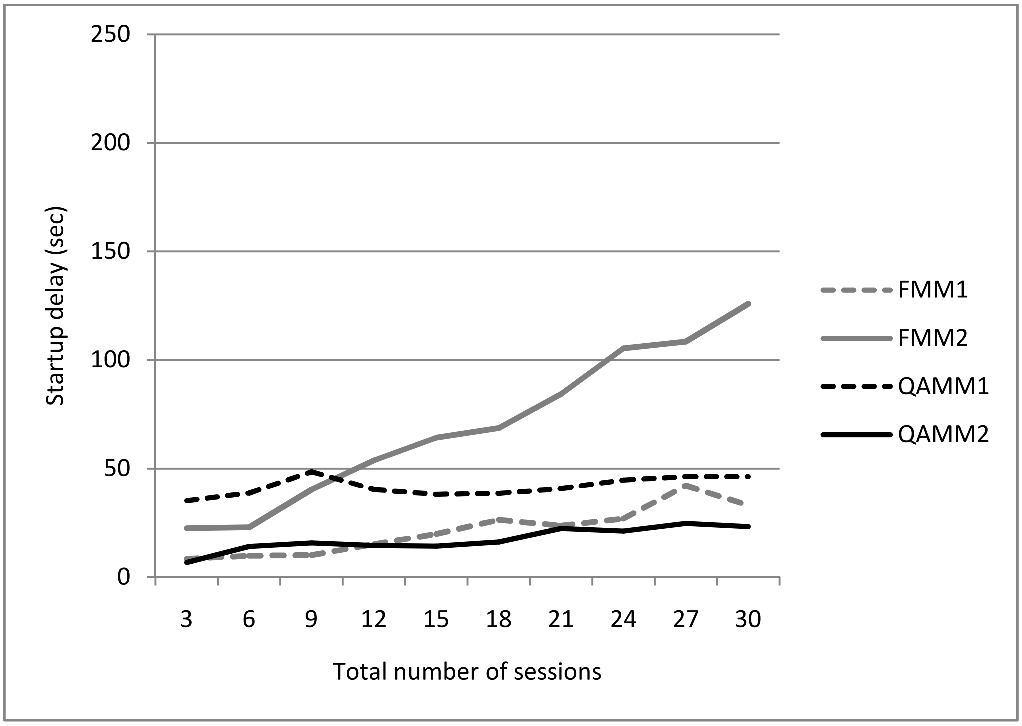

Figure 46: Average startup delay with DSL3 (2Mbps) configuration

6.4.2 Network Usage

Network usage shows a positive impact of the adaptation algorithm for all three configurations (see Figure 47, Figure 48 and Figure 49).

Network usage in general shows an upward trend with increasing session numbers across all profiles and configurations, as to be expected.

FMM1 shows the lowest network usage, but the strongest fluctuations across configurations. FMM2, the profile wit a media mix similar to that of the QAMM profiles, continuously shows the highest network usage. As expected, QAMM1 shows the least fluctuation. Significantly QAMM2 shows fluctuation similar to FMM2 for the DSL2 configuration, but on a slightly lower level.

The QAMM profiles show similar fluctuation for the dialup configuration (see Figure 47), but not for the DSL configurations. QAMM1 is continuously on a slightly higher level of average network usage with very little fluctuation, while QAMM2 shows an increasing fluctuation across configurations (see Figure 45and Figure 46).

In conclusion QAMM2 shows a lower level of average network usage than FMM2 with a moderate fluctuation for the DSL configurations.

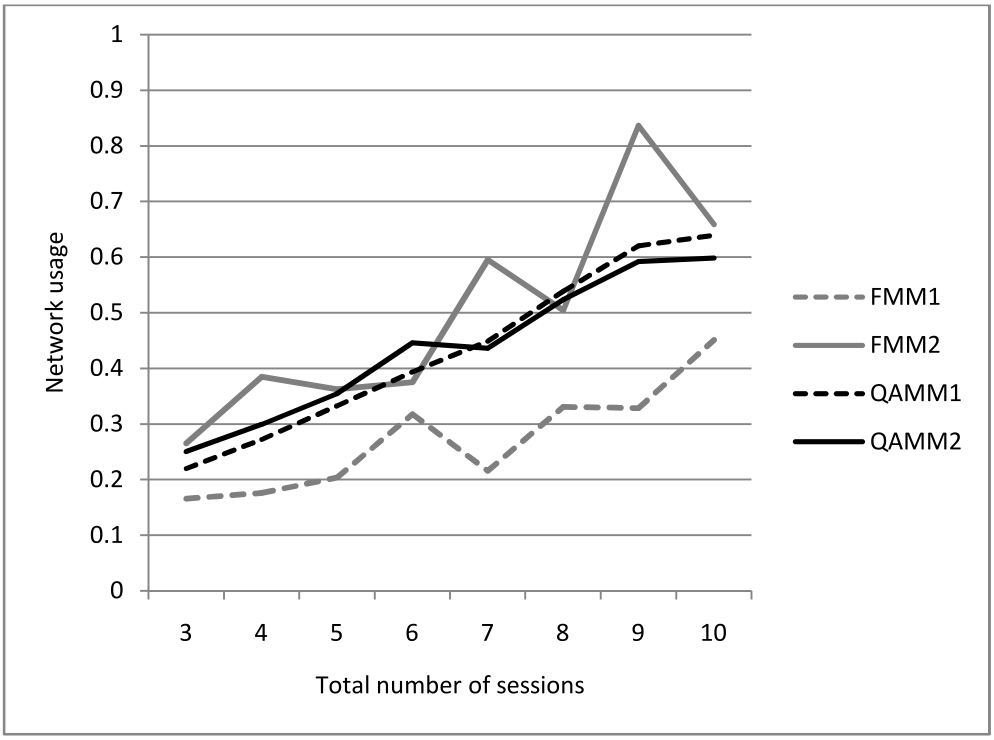

Figure 47: Average network usage with dialup configuration

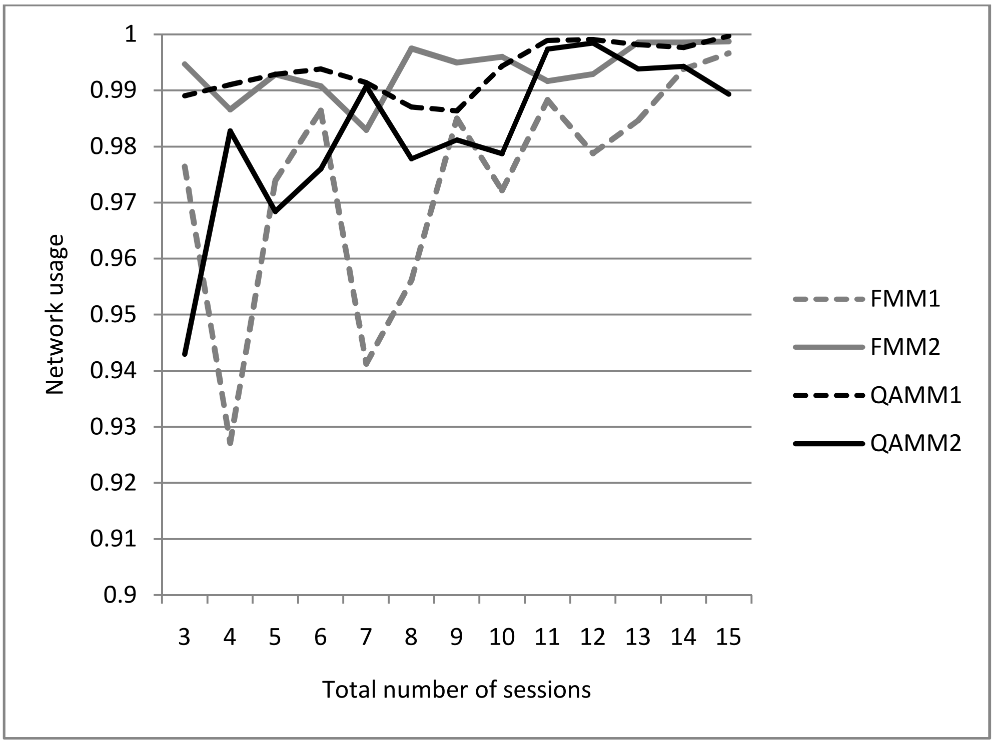

Figure 48: Average network usage with DSL2 configuration

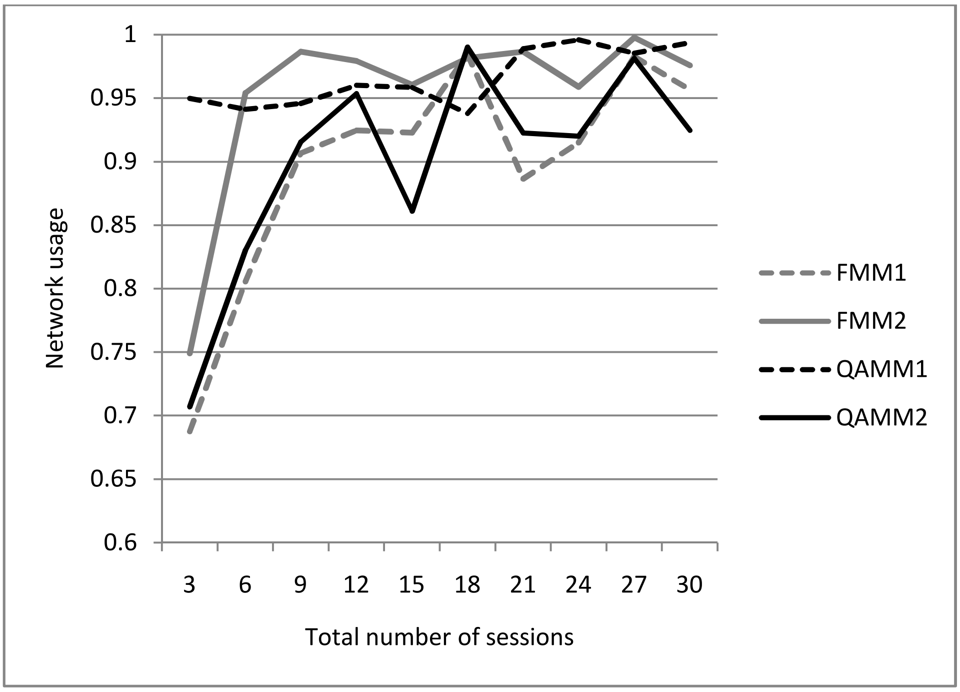

Figure 49: Average network usage with DSL3 configuration

6.4.3 Media Mix

The media mix has an impact on the average startup delays as well as the network usage. The following section shows that the QAMM profiles have a media mix similar to FMM2 and the reduction of startup delay is not attained at the cost of loss of media mix.

For the FMM profiles the mix is set to different percentages for each media while the QAMM profiles vary the mix depending on the execution of the algorithm. QAMM1 considers network conditions only, while QAMM2 also aims to maintain a mix of different media.

A comparison of the media mix for QAMM1 and QAMM2 (see Table 39, Table 40 and Table 41) shows that the different adaptation strategies emphasise certain media, almost regardless of the configuration. QAMM1 emphasises audio and always includes around 60% audio, while QAMM2 clearly emphasises illustrated text of which it includes 50-60% of the mix. Video is not strongly emphasised by either profile for any of the configurations. Overall QAMM1 has a mix of 15:65:20 while the mix for QAMM2 is 50:40:10.

The mix of the media explains some of the observations regarding network usage and startup delay. A considerably lower network usage for QAMM2 (see Figure

47, Figure 48 and Figure 11) corresponds to a decrease in video in QAMM2. The lack of peaks in QAMM2 indicates that the adaptation to network conditions avoids sending material with large bandwidth requirements when the network is busy. This also results in the lower startup delays when compared to FMM1.

Table 39: QAMM Media Mix for Dial-up

No Sessions	QAMM Profile 1 (%)			QAMM Profile 2 (%)		
	Text+ image	Audio	Video	Text+ image	Audio	Video
3	10.0	66.7	23.3	50.0	40.0	10.0
4	10.0	75.0	15.0	45.0	42.5	12.5
5	12.0	62.0	26.0	52.0	36.0	12.0
6	16.7	56.7	26.7	50.0	38.3	11.7
7	17.1	57.1	25.7	52.9	35.7	11.4
8	12.5	61.3	26.3	51.3	38.8	10.0
9	12.2	67.8	20.0	52.2	38.9	8.9
10	14.0	61.0	25.0	52.0	36.0	12.0

Table 40: QAMM Media Mix for DSL 2

No Sessions	QAMM Profile 1 (%)			QAMM Profile 2 (%)		
	Text+ image	Audio	Video	Text+ image	Audio	Video
3	6.7	43.3	50.0	50.0	30.0	20.0
4	7.5	52.5	40.0	50.0	35.0	15.0
5	10.0	38.0	52.0	54.0	36.0	10.0
6	10.0	50.0	40.0	53.3	36.7	10.0
7	11.4	60.0	28.6	54.3	30.0	15.7
8	13.8	55.0	31.2	57.5	30.0	12.5
9	14.4	62.2	23.3	57.8	32.2	10.0
10	16.0	56.0	28.0	56.0	40.0	4.0
11	16.4	65.5	18.1	59.1	30.9	10.0
12	16.7	60.0	23.3	57.5	35.0	7.5
13	17.7	60.0	22.3	57.7	34.6	7.7
14	17.1	57.1	25.7	62.9	29.3	7.9
15	22.0	62.0	16.0	63.3	32.7	4.0

Table 41: QAMM Media Mix for DSL 3

No Sessions	QAMM Profile 1 (%)			QAMM Profile 2 (%)		
	Text+ image	Audio	Video	Text+ image	Audio	Video
3	6.7	6.7	86.7	50.0	20.0	30.0
6	8.3	13.3	78.3	50.0	23.3	26.7
9	8.9	27.8	63.3	50.0	25.6	24.4
12	9.2	37.5	53.3	50.8	30.8	18.3
15	10.7	46.0	43.3	50.7	36.7	12.7
18	11.1	53.3	35.6	50.0	37.8	12.2
21	11.4	57.1	31.4	51.9	31.4	16.7
24	13.8	56.3	30.0	53.3	38.8	7.9
27	14.4	54.8	30.7	51.9	35.9	12.2
30	15.3	58.3	26.3	53.7	37.3	9.0

6.4.4 Confidence Intervals

A statistical analysis of variance (ANOVA) shows a normal distribution for all results and a constant variance. The P-value is >0.05 for a 95% confidence interval for all simulations – which indicates that the means are significantly different, confirming our hypothesis.

6.5 Conclusions

This chapter presents the results of the tests simulating e-learning traffic while applying the proposed adaptation algorithm. The algorithm considers network conditions and maintains a mix of different media.

The results indicate that the startup delays for multimedia e-learning courses can be reduced significantly for different bandwidth conditions, while maintaining a mix of media. This enables an engaging learning scenario, which in turn can improve the Quality of Experience.

The tests have shown that the adaptation algorithm enables network usage to be kept at a level that allows including media with medium to high bandwidth requirements, such as audio and video. This supports the idea that multimedia e-learning can be delivered to learners with low bandwidth connections, provided available bandwidth is taken into consideration.

The difference in the mix of media has an influence on the network usage as well as the startup delay. The next step of the research is to find out if the positive impact of the adaptation can also be confirmed with learners in user tests.

The media mix identified for the QAMM profiles and the fixed media profile FMM2 are used for user tests described in the following chapter.

7 User Test Results and Analysis

7.1 Objectives of the Evaluation

Testing investigates impact on the learning experience of:

4. Perceived quality of media and pedagogical approach
5. QoS-adaptive media
6. QoS-adaptive media mix

The Delphi study results in chapter 5 showed that QoS has not been considered a significant factor for the learning experience. The simulation results from the previous chapter showed a significant impact of the QAMM2 algorithm on startup delay and media mix. The user testing aimed to verify or disprove the findings from the simulations and the Delphi study. The test results were analysed comparing the feedback of the different stages and investigated the impact of QoS on the learning experience of real users.

The setup of the user tests aimed at to be as close to a real learning situation as possible. The course was advertised to DCU students and students of DCULS, the on-campus language services company as a free pilot course in "Academic Writing" for non-native speakers of English with intermediate to advanced English. All sessions of the course followed the same basic structure; an introduction, in either medium, was followed by different learning activities such as exercises, tests and collaborative work.

Selection of participants was intended to provide a group with similar knowledge level, motivation, educational background, mix of learning styles, age and a minimum digital literacy.

The user test course was offered in Moodle LMS with learning material simulating the respective adaptation. User tests were run as so-called Wizard of Oz user studies [122]. In a Wizard-of-Oz study a researcher simulates the behaviour of a computer system; for this research the adaptation to network conditions was simulated.

The first stage of user testing provided feedback on a non-adaptive multimedia course, following the media mix used in the FMM2 profile of the simulations. It also tested the suitability of the pedagogical approach. The second stage investigated adaptation of the course material to QoS, presenting course material with the highest bandwidth requirements that can be sent. The final stage of user testing provided course material adapted to both QoS and media mix. Each stage was several units long, to make sure the mix in media and the different quality adaptations can be noticed by the participants.

7.2 Experimental Setup

7.2.1 Participants

The participants' age ranged between 20 and 40 years with the majority between 20 and 30 years and only two participants older than that.

There was a wide selection of different nationalities involved due to the recruitment of participants through the Language School, the international office and the postgraduate society – all mainly used by either non-English-speaking or non-European students.

All participants had at least an undergraduate degree; some also had completed a Master degree. They came from different areas of study; 35% have a degree in Business, Languages and Humanities, 23% had a degree in Technology and 42% had a degree in Science. The Felder learning styles assessment [61] shows that the majority of the participants had a very weak preference for the different dimensions of the Felder's learning styles model (see Table 42). According to Felder, students with mild preferences do not show typical behaviour for the respective dimensions. None of the participants had a strong preference for more than one dimension. This means that the results should not be affected by preferences for any kind of learning style.

Table 42: Strength of Learning Styles Preferences

Active-Reflective					Sensing-Intuitive				
Strong Act	Mod Act	Mild	Mod Refl	Str Refl	Str Sens	Mod Sens	Mild	Mod Int	Str Int
4%	11%	74%	7%	4%	4%	22%	59%	15%	0%

Visual-Verbal					Sequential-Global				
Strong Visual	Mod Visual	Mild	Mod Verbal	Strong Verbal	Strong Seq	Mod Seq	Mild	Mod Global	Strong Global
15%	26%	52%	0%	7%	0%	11%	56%	33%	0%

44% of the participants were male, 56% were female.

Previous e-learning experience of the participants varied; 29% had no previous e-learning experience, 41% had used e-learning once and 30% had used e-learning more than twice previously. Interestingly the 29% with no experience were mostly Science students. These figures also mean that two third have had previous e-learning experience.

The digital literacy assessment was part of the participant profile to be able to consider the use of new tools as challenge for the participants. The assessment is based on Hargittai's work [92] and considers self-perceived skills for digital and online activities. 30% of the participants had basic skills, 44% had intermediate skills and 26% have advanced skills. All the participants had previous working experience with a computer.

In summary the tests were run with adult students, aged between 25 and 40, with good computer literacy, basic to intermediate knowledge of the subject (EFL), intermediate to advanced English skills as assessed by the English pre-test and balanced learning style profiles. The participant profile with assessment of digital literacy and demographics as well as the English assessment and the Learning Styles Questionnaire can be found in the appendix.

7.2.2 Test scenario

The test sessions were organized as an English course with a focus on academic writing. The test course was branded "LUCie Intermediate to Advanced English

Course” and advertised with a flyer sent out by the International Office and the Office for Graduate Research (see Appendix). LUCie stands for Learner, User and Customer in e-learning. The course design was developed in cooperation with teachers from the on-campus language school. The course was set up in several units covering different aspects of academic writing and intermediate to advanced English.

1-hour sessions were offered three times a week. To accommodate all participants there were three groups scheduled for different times. The sessions were running from the beginning of May until the beginning of August. The number of participants varied between 20 and 40.

During the sessions the participants worked through the new tasks and materials in the Moodle course. The tasks and materials usually included some information presented using different media types followed by different activities and tests. The media theory model supports the concept that the human brain processes information best if it is taken in using both input channels, visual and verbal. If information input feeds the same channel twice, for example a speaker who uses a text slide, the information processing is not optimal. Therefore audio and text with images or a video was used, providing optimal information input. The activities included learning to use a new mind-mapping tool (FreeMind), searching for information, writing and correcting text in the wiki or the forum and tests. The tests varied between multiple choice questionnaires, true-false questions and cloze texts

The researcher conducting the survey was present in the room during the sessions to provide support for technical problems. Further questions could be asked in the Moodle chat to avoid too much noise due to conversations, which might have interrupted other participants’ concentration. The chat also made answers to the questions accessible to everybody else and avoided having to answer the same question several times.

The course consisted of different types of activities and included listening to illustrated podcasts, watching videos, reading illustrated text, creating mind maps, writing into a wiki, learning to use a wiki or mind mapping software, writing essay-type answers, develop an initial structure for a paper, writing short paper drafts on self-selected topics, identify what type or which section of a paper an extract was sourced from, correcting other participants paper drafts, expanding on existing entries in the wiki, answering drag-and-drop exercises and multiple choice questions.

7.2.3 Test environment

To embed the test units in a real learning environment the test units were run in one of the regular student laboratories.

The laboratory-network setup used for testing involved fourteen PC desktops with Dual Core (Pentium D) processors and 2 GB memory each. The browser used was Mozilla Version 3.6. The monitor screen size was 17". The different network conditions were simulated using Firefox throttle, a Mozilla bandwidth utilization throttling plug-in.

The course ran in Moodle version 1.9.8 on Sony VAIO PFG-3C1M as server. The course used Moodle wiki, Moodle forum, Moodle chat, Moodle exercises and lessons.

When students entered the test lab the course login was open in the Firefox browser to make sure no other browser was used and Firefox Throttle could be used for bandwidths manipulation. Firefox Throttle provides four levels of maximum bandwidth for upload and download. These levels are Dial-up (56kbps), DSL/Cable (256kbps), DSL/Cable (768kbps) and T1 (1.5Mbit). For courses with no adaptation the plug-in was set to 256kbps download. For QAMM1 and QAMM2 download was set to T1.

Further manipulation of the learning materials resembling bandwidth bottlenecks was achieved by a media converter. It allows selection of the compression H264.4. This compression was chosen to enable feed into another engineering research project. Next the quality level was chosen; either low, medium, optimal or high. For no adaptation some of the audio and video files were saved at medium quality. Medium quality causes videos to get blurry; people are still visible in acceptable quality, but text is hard to read. The audio sound is slightly patchy. For QAMM1 and QAMM2 audio and video files were saved with optimal quality.

The media mix used for no adaptation was the FMM2 profile from the simulations and the media mix resulting from the simulations of DSL2 for QAMM1 and QAMM2 adaptation. The units with no adaptation provided a media mix of roughly equal time shares of text, audio and video, with the text share slightly bigger. The QAMM1 adaptation contained very little text, mostly audio and some video, resembling a media distribution of 15:55:30 for text, audio and video. For the QAMM2 adaptation roughly half of the learning materials were text, then some audio and some video, resembling a media distribution of 55:30:15 for text, audio and video.

The settings outlined above will impact on generaliability of the results, because they require a system that either provides materials in 3 different media types or provides mechanisms to extract text with images and audio with images from a video. The latter would require developing a video that can be taken apart like that, and still be suitable learning material in either media format. This would heavily impact on storyboarding and overall cost. However recent developments regarding speech-to-text technology [205] and identifying relevant frames in a video stream [80] allow for a scenario that is based on the provision of one media to be used to create different types of media mix.

7.3 QoE Evaluation Tools

According to the QoE model as described in chapter 4 Quality of Experience is affected by two factors, learning and flow experience, and both factors are in turn affected by QoS. The QoE evaluation followed the probe model outlined in chapter 4. It consists of course probing, a post survey and pre-post learning tests evaluating perceived quality of service (QoP), flow experience, learning and experience.

QoS Indicator for QoS is QoP. The unit survey specifically asks for feedback on the quality of the different media. The post survey inquires about the perceived speed of the website and response time to user actions.

Flow Flow indicators are time distortion, immersion, the balance of skill and challenge and enjoyment. Time distortion is assessed with questions asking about the perception of time passing by. Immersion related questions ask for two levels of immersion. The first level is losing awareness of most events around us. The second level is complete immersion in the activity on the screen without noticing anything happening in our immediate surroundings. Skill and challenge was assessed by questions inquiring whether the learners considered the challenges suitable for their knowledge level. Enjoyment was continuously assessed with a 4-point Likert scale labelled with emoticons. Post survey questions assessed aspects of enjoyment such as whether the course was interesting, attractive and provided new information.

Learning Learning is indicated by pre-post assessment and perceived learning. The pre-test assessed knowledge about academic writing. The post-test assessed academic writing skills and knowledge about the topic. Perceived learning asked the learner for an evaluation of their progress.

Experience Finally experience indicators are overall experience and expectations. The unit survey asked whether the particular session met the learner expectation. The post survey asked whether the course had fulfilled expectations posted during the first session.

Table 43 provides an overview of factors, indicators and measurement.

Table 43: Overview factors, indicators, measurement

Factor	Indicator	Measurement
QoS	Quality of Perception (QoP)	Unit Survey Probing Post Survey Statements 2, 3, 13
Flow	Time distortion	Unit Survey Probing Post Survey Statement 14
	Immersion	Post Survey Statements 15, 16
	Skill : challenge	Unit Survey Probing
	Enjoyment	Course Probing Post Survey Statements 1, 4, 5, 8
Learning	Pre-assessment	Pre-test
	Post-assessment	Post-test
	Perceived Learning	Post Survey Statements 17, 18, 21
Experience	Expectations	Unit Survey Probing Post Survey Statement 22
	Experience	Unit Survey Probing Post Survey Statements 12, 19, 20
Usability	Navigation Task support	Unit survey probing (unit 1 and 2 only) Post Survey Statements 6, 7, 11

7.3.1 Course Probing

The course probing consisted of two main parts, the enjoyment sampling built into the course material and an end of session online questionnaire.

The enjoyment sampling collected feedback with a 4-point Likert scale labelled - enjoyable, - alright, - mixed and - boring. The course probing was collected after each individual activity. Thereby students gave the same feedback whether they followed the lesson outline or selected the exercises randomly. An example for a lesson outline can be found in the appendix.

The end of session questionnaire collected feedback on quality of perception, aspects of flow and aspects of learning. Feedback on overall experience, learning support, meeting of expectations and time distortion was collected with 4-point Likert scales labelled "very good", "good", "a bit of both" and "bad". Feedback on skill-challenge ratio, perceived quality of the media and time distortion was collected with a 5-point Likert scale labelled “fully agree”, “agree”, “not sure”, “slightly disagree” and “disagree”.

The end of session questionnaires was collected after each 1-hour session. A sample of the end-of-session questionnaire can be found in the appendix.

7.3.2 Post-Survey

The post survey investigated the main concepts of the QoE model with 22 questions. The survey was a questionnaire with 4-point Likert-type scales labelled “I strongly agree” and “I strongly disagree” at the extremes. It was sent out to participants after they completed the course. The survey can be found in the appendix.

7.3.3 Pre-Post-Test Tools

The pre-test was a set of online questionnaires testing the level of English and knowledge about academic writing. The English test served to confirm that students had sufficient knowledge of the language to follow the course. The English test is a standard test used by DCU Language Service as a placement test for their IELTS (International English Language Testing System) courses. All students admitted to the course had passed the pre-test English. These results were not considered further for the analysis.

The academic writing pre-test was the actual pre-test and was compared with post-test results afterwards. The test required learners to answer questions about academic writing and a grammar and vocabulary test targeting typical errors of non-native English speakers. The academic writing post-test was a paper-based test consisting of 4 tasks. The test required learners to identify academic writing structures, errors in writing and to apply their knowledge about academic writing. Both tests were developed in cooperation with the DCU Language Service, which regularly offers courses in academic writing. The tests can be found in the appendix.

Results and analysis of the two tests are presented in a comparison, because they show the learning results of the course.

7.4 Course Probing - Results and Analysis

This section describes the results of the statistical analysis, statistical tests applied and the interpretation of the results. The statistical analysis was carried out with SPSS and followed the procedure for the different tests as outlined in [63]. The decision on appropriateness of the statistical tests is based on previous research [35] [84] [94] [109] [223] and statistical literature [63].

7.4.1 Statistical Tests

ANOVA was considered initially for data analysis, but a normality distribution of the data could not be confirmed. The Kruskal-Wallis test is the non-parametric equivalent to ANOVA [63] and was therefore applied to analyse the results.

The Kruskal-Wallis results show whether a difference exists between the three adaptation schemes no adaptation, QAMM1 and QAMM2. The Mann-Whitney test was used as a so-called post-hoc test for the Kruskal-Wallis tests to follow up on these results. Additionally the Jonckheere-Terpstra test indicates trends in the results. All tests were run in SPSS17 [63]. The results from the two tests can be used to calculate trend and effect size. The effect size comparing two of the adaptation schemes can be calculated using the z-score from the Mann-Whitney test. Adaptation 1, 2, and 3 represent the different adaptation schemes. The coding variables used are 1 for no adaptation for a FMM2 profile, 2 for QAMM1 adaptation, adapting to network conditions without consideration of the media mix and 3 for QAMM2 adaptation.

To calculate the effect across all three schemes the standard statistic from the Jonckheere-Terpstra test is used.

The detailed values for all statistical tests can be found in the appendix.

7.4.1.1 Effect size (Mann-Whitney)

The effect size *r* has a value between 0 and 1. Criteria for the effect size are <.3 for a small effect and >.5 for a large effect. Equation 1 shows how to calculate the effect size *r*.

Equation 1

$$r_{\mathrm{NoAdapt-QAMM1/QAMM2}} = \frac{\mathrm{z-score}}{\sqrt{\mathrm{N}}}$$

The z-score is taken from the results of the Mann-Whitney test.

N represents the number of participants in both groups.

All effects are reported at a significance level of $p < .05$.

The r value is calculated for the effect between no adaptation and QAMM1 adaptation and for no adaptation compared to QAMM2 adaptation.

7.4.1.2 Effect size (Jonckheere-Terpstra)

The effect for the series of adaptations can be calculated using the Jonckheere test, using an equation similar to Equation 1. N then represents the participants in all the groups and instead of the z-score the standard J-T statistic is applied (see Equation 3).

Equation 2

$$r_{\text{Jonckheere}} = \frac{\text{Standard J} - \text{T statistic}}{\text{N}}$$

7.4.1.3 Testing for trends (Jonckheere-Terpstra)

Equation 3 shows how to calculate the Jonckheere z-score.

Equation 3

$$z = \frac{(\text{JT statistic} - \text{mean JT statistic})}{\text{Standard Deviation JT statistic}}$$

Ignoring the sign, values >1.65 indicates a significant trend. For values >1.65 a negative sign of the z-value indicates a trend of descending medians; the medians get smaller as the value of the coding variable gets bigger. A positive sign indicates a trend of ascending medians; the medians get bigger as the value of the coding variables get bigger.

A short overview how the statistics were calculated is provided with the example of the results for enjoyment.

7.4.2 Results Enjoyment

The Kruskal-Wallis Test provides the test statistics (see Table 44)

Table 44: Test Statistics Kruskal-Wallis Test Enjoyment

Test Statistics[a,b]

	Rating
Chi-Square	6.127
Df	2
Asymp. Sig.	.047
Exact Sig.	.056
Point Probability	.009

a. Kruskal Wallis Test

b. Grouping Variable:
Adaptation Type

The table shows the test statistics H, which in SPSS is labeled chi rather than H, because of its distribution. The next line provides the degrees of freedom. In the following line the significance is shown, which is <.05. Therefore we can say that enjoyment was significantly affected by the adaptation ($H(2) = 6.13$; $p<.05$).

The next set of values comes from the Jonckheere test (see Table 45). The Jonckheere test tests for an ordered pattern of the medians of the groups we are comparing. Here we are comparing impact of the three types of adaptation on enjoyment and this test analyses whether there is a trend.

Table 45: Results Jonckheere Terpstra Test Enjoyment

Jonckheere-Terpstra Test[a]

	Rating
Number of Levels in Adaptation Type	3
N	60
Observed J-T Statistic	745.500
Mean J-T Statistic	600.000
Std. Deviation of J-T Statistic	65.790
Std. J-T Statistic	2.212
Asymp. Sig. (2-tailed)	.027
Exact Sig. (2-tailed)	.023
Exact Sig. (1-tailed)	.011
Point Probability	.000

a. Grouping Variable: Adaptation Type

The first line shows that the test considers three different levels of a data type called adaptation. These three levels represent no adaptation, QAMM1 adaptation and QAMM2 adaptation.

To test for trends we use Equation 3 to convert the values to a z-score

$$\mathrm{z} = \frac{(\text{JT statistic} - \text{mean JT statistic})}{\text{Standard Deviation JT statistic}}$$

with the values provided in the test table (see Table 45). The J-T statistic has the value 745.5, the mean J-T statistic has the value 600 and the standard deviation of the J-T statistic is 65.79. We are looking for a value >1.65 for a significant result. The sign before the value tells us whether it is a trend of ascending medians (+) or a trend of descending medians (-). In this example an ascending trend means that more adaptation (no adaptation, QAMM1 finally QAMM2) means more enjoyment. This gives us the trend across all adaptations. To test how big the effect r is, we use Equation 2 and convert to the r value.

$$\mathrm{r}_{\text{Jonckheere}} = \frac{\text{Standard J} - \text{T statistic}}{\mathrm{N}}$$

The standard J-T statistic is 2.212, N is 60. The r value gives us the effect size for the complete tests. The r value is .29, which is below .3 and therefore represents a small effect.

To also analyze the effect size between pairs of adaptation the results of the Mann-Whitney test is used. Here we use two tables; one with the test statistics for a comparison between no adaptation and QAMM1 adaptation (see Table 46) and another one for a comparison between no adaptation and QAMM2 adaptation (see Table 47).

Table 46: Mann-Whitney Test Enjoyment; no adaptation:QAMM1

Test Statistics[b]

	Rating
Mann-Whitney U	195.500
Wilcoxon W	405.500
Z	-.139
Asymp. Sig. (2-tailed)	.889
Exact Sig. [2*(1-tailed Sig.)]	.904[a]
Exact Sig. (2-tailed)	.833
Exact Sig. (1-tailed)	.416
Point Probability	.016

a. Not corrected for ties.

b. Grouping Variable: Adaptation Type

Table 47: Mann-Whitney Test Enjoyment; no adaptation:QAMM2

Test Statistics[b]

	Rating
Mann-Whitney U	134.000
Wilcoxon W	344.000
Z	-1.931
Asymp. Sig. (2-tailed)	.054
Exact Sig. [2*(1-tailed Sig.)]	.076[a]
Exact Sig. (2-tailed)	.075
Exact Sig. (1-tailed)	.038
Point Probability	.012

a. Not corrected for ties.

b. Grouping Variable: Adaptation Type

To calculate r we use Equation 1

$$r_{NoAdapt-QAMM1/QAMM2} = \frac{z - score}{\sqrt{N}}$$

To calculate $r_{\text{No adaptation-QAMM1}}$ the z-score is -.139 (see) and N is 40 since both adaptations were tested with 20 participants each. To calculate $r_{\text{No adaptation-QAMM2}}$

the z-score is -1.931 (see) and N is again 40 since both adaptations were tested with 20 participants each. This gives us $r_{\text{No adaptation-QAMM1}} = -.022$ and $r_{\text{No adaptation-QAMM2}} = -.31$.

In summary the Jonckheere test showed a significant trend in the data. Enjoyment increased with the adaptation and the effect across all adaptations is small; J = 745.5, z = 2.21, r = 0.29.

The Mann-Whitney test showed that in detail there was no effect of QAMM1 adaptation (U = 195.5, r = -.022), while there was a medium effect of QAMM2 adaptation (U = 134, r = -.31).

In summary, QAMM1 does not affect enjoyment of the learners, while QAMM2 has a significant positive effect.

7.4.3 Results for Experience

Experience was significantly affected by the adaptation (H(2) = 8.186; p<.05). Jonckheere's test showed a small trend in the data. The experience improved with the adaptation, but the effect across all adaptations is very small; J = 647.5, z = .07, r = 0.09. The Mann-Whitney test showed in detail a medium effect of QAMM1 (U = 128, r = -.33). QAMM2 showed a small effect, however outside the significance level of .05.

In summary, QAMM1 affected the experience of the learners, while QAMM2 did not reach the level of significance of <.05.

7.4.4 Results for Expectations

Expectation was significantly affected by the adaptation (H(2) = 10.48; p<.05). Jonckheere's test showed a significant ascending trend in the data. Expectation values increased with the adaptation and there was a medium effect across all adaptations; J = 804, z = 2.96, r = 0.38. The Mann-Whitney test showed that in detail there was a very small effect of QAMM1, however outside the level of significance (U = 185, r = -.068), while there was a large effect of QAMM2 (U = 88, r = -.53).

In summary, expectations of the learner were less fulfilled with QAMM1, while QAMM2 had a significant effect and expectations were fulfilled.

7.4.5 Results for Time Distortion

Time distortion was significantly affected by the adaptation (H(2) = 11.72; p<.05). Jonckheere's test showed a significant ascending trend in the data. Time distortion increased with the adaptation and there was a medium effect across all adaptations; J = 769.5, z = 2.47, r = 0.32. The Mann-Whitney test showed that in detail there was a small effect of QAMM1, however outside the level of significance (U = 168.5, r = -.-0.15), while there was a medium to large effect of QAMM2 (U = 97, r = -.49).

In summary, QAMM1 did not improve time distortion, while QAMM2 showed a large effect on time distortion.

7.4.6 Results for Skill-Challenges Ratio

The Skill-Challenge ratio was not significantly affected by the adaptation (H(2) = .291; p>.05). Jonckheere's test showed no trend in the data. Time distortion increased with the adaptation and there was a medium effect across all adaptations; J = 632, z = 0.47, r = 0.06. The Mann-Whitney test showed that both, QAMM1 (U = 184.5, r = -.07) and QAMM2 (U = 184, r = -.07), had only a very small effect.

In summary, the adaptation did not affect how learners rated the skill-challenge ratio. This argues that the material presented were truly equivalent.

7.4.7 Results Quality of Perception

Quality of Perception was significantly affected by the adaptation (H(2) = 16.18; p<.05). Jonckheere's test did not show a trend in the data; J = 655, z = 0.79, r = 0.10. The Mann-Whitney test showed that in detail there was a medium to large effect of QAMM1 (U = 89, r = -.49), while there was only a small effect of QAMM2 (U = 160.5, r = -.18) however outside the level of significance of .05.

In summary, QAMM1 does not improve the experience of the learners significantly, while QAMM2 has a significant effect.

7.5 Post Survey

The post survey collected feedback on several factors of the proposed QoE model at the end of user testing. It contains elements to identify flow experiences, enjoyment, experience, perceived learning, Quality of Perception and usability. Factors, indicators and measurements are summarized in Table 43. The post survey complemented the pre-post learning assessment and the continuous assessment of enjoyment, experience, expectations, skill-challenge ratio, time distortion and Quality of Perception during the user tests.

The post survey data was collected from 15 users who completed all the sessions. The post survey was a questionnaire including 22 statements with 4-point Likert-type scales labelled “I strongly agree” and “I strongly disagree” at each extreme. The 4-point scale forces choices and was selected to avoid neutral answers. The questionnaire design is based on previous flow research [198] and research on customer satisfaction [87] [90] [104].

The results of the post survey are not linked to a specific adaptation policy. The survey reports what users remember after the course is completed. The results show that there is a different perception during the course, assessed with the course probing, and after the course, assessed with this post survey.

7.5.1 Flow Survey

Three survey items investigated flow and in particular time distortion and immersion (see Table 48). The two statements about immersion aimed to explore how much users felt immersed. Immersion in a world created by the course website is intensity usually found in online games, but not in course websites and would indicate very strong immersion. Being unaware of the surroundings indicates much less immersion, though it still indicates immersion and a focus on the task.

Table 48: Flow Survey Statements

S14	While I was browsing the course pages, time seemed to go by very quickly.
S15	While browsing this course, I was not aware of my immediate surroundings.
S16	I felt that I was in the world created by the course web site.

Statement 14 and statement 15 received a mean value of 1.87; statement 15 and statement 16 received a mean value of 2.13 (see Table 49). These results indicate general agreement with all three statements.

Looking at the results for statement 14 in detail shows that there are three users who disagreed, while everybody else apparently felt that time went by quickly and therefore agreed with the statement. These results can be confirmed by user observations; often participants had to be reminded to conclude their sessions.

Two users expressed strong disagreement with statement 15, indicating that they were constantly aware of their surroundings, while all other users confirmed immersion in the activity.

Statement 16 received disagreement from six users, which is more than a third of the users. Nevertheless the majority of participants indicated strong immersion in the activity, which is unusual for learning websites.

Table 49: Flow Survey Results

	I strongly agree 1	2	3	I strongly disagree 4	Mean	Mode
S14	5	7	3	0	1.87	2
S15	6	7	0	2	1.87	2
S16	4	5	6	0	2.13	3

Looking at the individual responses to all three flow related statements, and in particular the two statements investigating immersion, a few peculiarities stand out. Out of the six users who did not experience immersion at all (S16) only one also disagreed with the light immersion (S15). This is in line with the expected result that immersion can be expected, but not necessarily strong immersion. One user disagreed with all three statements, which indicates the course was a rather painful experience. The mean value and the mode value are very close for statements 14 and 15; while the mode value is considerably lower for statement 16 (see Table 49). In summary most users confirmed a flow experience.

7.5.2 Enjoyment Survey

Four items investigated enjoyment (see Table 50) as one of the flow indicators. Statement 1 focused on the overall experience. Statements 4, 5, and 8 explored individual aspects contributing to enjoyment such as enjoyment in general and whether users found the course interesting and attractive while providing new information.

Table 50: Enjoyment Survey Statements

S1	Overall, I enjoyed LUCie.
S4	The course is interesting.
S5	The design of the course is attractive.
S8	The course provided some information that is new to me.

Mean and mode values are very similar (see Table 51). Statement one received a mean value of 1.87, confirming most users enjoyed the course. Statement four has a mean value of 1.73, showing that most users found the LUCie course interesting. The design of the course was perceived as attractive and this resulted in a mean value of 1.60 for statement five as well as a mode value of 1, indicating strong agreement. Although the mean value of statement eight of 1.80 is lower than those of the last two statements, it received the least disagreement of all enjoyment-related statements.

There was no strong disagreement with any of the enjoyment-related statements. One user indicated disagreement with statements 1, 4 and 5. This user gave an average feedback of 2.5 for all statements, which is the lowest evaluation value. Interestingly the same user expressed satisfaction with the course in the interview following the post survey.

Table 51: Enjoyment Survey Results

	I strongly agree 1	**2**	**3**	**I strongly disagree 4**	**Mean**	**Mode**
S1	5	7	3	0	1.87	2
S4	6	7	2	0	1.73	2
S5	8	5	2	0	1.60	1
S8	4	10	1	0	1.80	2

In summary the results indicate that the course was interesting, attractive and provided new information, which made it enjoyable.

7.5.3 Experience Survey

Four items presented experience-related statements (see Table 52). Statements explored satisfaction with the website, user retention and whether expectations were fulfilled.

Table 52: Experience Survey Statements

S12	I felt efficient when I was using the web site.
S19	After attending the course, I want to find out more about academic writing.
S20	I would like to return to the course web site for information on academic writing.
S22	In the first session you were asked to outline your expectations. Please read the copy of your submission. Looking back, did the course meet your expectations?

Statement 12 received a mean value of 2.53, which indicates that the participants did not feel efficient using the website. All participants except for one would were inspired by the course to find out more about academic writing. This is reflected in a mean value of 1.53 for statement 19, which is the best result of all the statements and indicates strong agreement. Statement 20 has a mean value of 1.73; except for one all participants would like to return to the website. This extremely positive feedback is interestingly followed by statement 22 with a low mean value of 2.40. The course did not meet the expectations of almost half of the participants.

Table 53: Experience Survey Results

	I strongly agree 1	2	3	I strongly disagree 4	Mean	Mode
S12	3	3	7	2	2.53	3
S19	8	6	1	0	1.53	1
S20	6	8	0	1	1.73	2
S22	2	6	6	1	2.40	2, 3

The results present strongly varying feedback (see Table 53). Participants did not feel efficient and expectations they had were not fulfilled. The expectations were collected for each participant as a forum posting at the beginning of the course. Each participant was given those expectations for evaluation in the post survey. On the other hand most users would like to return to the course website for information on academic writing and felt inspired by the course to learn more about academic writing.

7.5.4 Perceived Learning Survey

Three items assessed perceived learning (see Table 54). Three of the statements on perceived learning explored the self-perception of the users, while the remaining two statements investigated learning and knowledge gained through the course.

Table 54: Perceived Learning Survey Statements

S17	After visiting the course, I feel that I have learned more about academic writing.
S18	I have gained more knowledge about academic writing attending the course.
S21	After visiting the course site, I am confident that I can write academic texts.

All statements related to perceived learning show a mean value of 1.87, with different mode values though (see Table 55).

Table 55: Perceived Learning Survey Results

	I strongly agree 1	2	3	I strongly disagree 4	Mean	Mode
S17	7	3	5	0	1.87	1
S18	6	5	4	0	1.87	1
S21	5	7	3	0	1.87	2

The result for statement 17 implies that two third of the participants had the feeling they learned more about academic writing and a mode value of 1 mirrors that almost half of the participants strongly agree wit this statement. Five users showed moderate disagreement with the statement.

Most users had the impression they gained more knowledge how to write academic texts and agreed with statement 18. Two users disagreed with both those statements, indicating they neither learned nor gained more knowledge about academic writing.

Statement 21 has a lower mode value compared to the previous two statements, but has only a fifth of the participants disagreeing moderately. The majority of the users feel more confident writing academic text.

In summary close to a third of the participants moderately disagree that they learned more about academic writing, although the majority feels confident to write academic texts after attending the course.

7.5.5 Quality of Perception Survey

Three items explored QoP user feedback (see Table 56). The statements differentiate between general impressions of the speed of the website, response to user actions, including opening an audio or video file and loading of a web page.

Table 56: Qualityof Perception Survey Statements

S2	The web site speed is fast.
S3	There is little waiting time for the web pages to load.
S13	The web site's response to my actions (such as clicking a link) was fast.

Statement 2 and statement 13 received a mean value of 1.67 and statement 3 received a mean value of 2.0 (see Table 57). This indicates general satisfaction with the speed of the website. A third of the participants disagreed with statement 3; they found loading times for web pages too long. However the mode value for the statement shows that more than a third of participants agreed strongly that there is little waiting time for web pages to load.

All participants agreed that the response to user action was fast.

Table 57: Quality of Perception Survey Results

	I strongly agree 1	2	3	I strongly disagree 4	Mean	Mode
S2	7	6	2	0	1.67	1
S3	6	4	4	1	2.00	1
S13	5	10	0	0	1.67	2

In summary these results reflect that the purposely built-in startup delays for some of the units did not make a lasting impression (see Table 57).

7.5.6 Usability Survey

Three items explored the usability of the website (see Table 58). Usability was not part of the proposed QoE model. During the pre-tests and throughout the user tests usability issues came up frequently. Moodle, the learning management system (LMS) used for the user tests was chosen, because it is the system in use at the university. Also there was an expectation that a system used by many institutions in higher education would provide an acceptable level of usability. Most usability issues are directly rooted in the LMS.

Table 58: Usability Survey Statements

S6	I had no problem finding what I wanted.
S7	Navigation of the course was simple and easy.
S11	I felt that I had the freedom to go anywhere in the web site.

Usability got a very mixed response, including strongest disagreement (see Table 59). Most people had problems finding what they wanted, which resulted in a mean value of 2.43 for statement 6. Statement 7 received a mean value of 2.80, which confirmed many of the comments in the chat and requests for help during the sessions. It stands out that 5 participants expressed strong disagreement. Half of the users did not feel that they could go everywhere on the website; statement 11 received a mean value of 2.33.

Table 59: Usability Survey Results

	I strongly agree 1	2	3	I strongly disagree 4	Mean	Mode
S6	3	3	8	1	2.47	3
S7	1	6	3	5	2.80	2
S11	4	4	5	2	2.33	3

The navigation was confusing for many of the users. This became obvious in many of the chat comments and was expressed clearly during the focus group type discussion at the end of the user tests. Sometimes users got lost, going back from an activity to a course page. Users even felt they could not go everywhere on the website. The navigation changes from the left of the screen to the top. The navigation on the left includes all top level items, which is replaced with bread-crumbs navigation on the top of the page for activity pages.

7.5.7 Summary Post Survey Results

The results show that immersion in the course was possible for most users and they also enjoyed the course. The experience was mixed though. On the one hand the course inspired users to learn more about the topic and they wish to return to the website for future reference. On the other hand some users considered the course inefficient and indicated that their expectations were not met. The learning-related questions showed that most users have a low self-perception of their knowledge, but they indicated that they learned something and feel more confident to write academic texts after the course. The website speed was considered good and loading times for pages fast. The usability of Moodle was considered poor by most users, in particular the navigation of the website.

7.5.8 Analysis Post Survey

For the relationships between learning, flow and experience the study produced results which add to the findings of previous work in this field [198] [150]. The analysis and conclusion looks at the results of the user tests along the relationships in the proposed QoE model. The regression analysis examines the impact of learning on experience and the impact of flow on experience. It also considers the impact between flow and learning. Finally it considers the impact of QoS/QoP on flow, learning and experience. QoS is used synonymously with QoP as the post survey could only ask for the perceived quality.

To analyze the data a regression analysis was carried out. The results of the regression analysis are reported for the different relationships in the following. The detailed tables with the results of the regression analysis can be found in the appendix.

7.5.8.1 Impact of Learning on Experience

Learning accounts for 45% of the experience, makes a significant contribution to it and predicts experience significantly well ($R^2 = .455$; $F = 10.866$).

7.5.8.2 Impact of Flow on Experience

Flow accounts for 27.2% of the experience and also makes a significant contribution, predicting experience significantly well ($R^2 = .272$; $F = 4.850$).

7.5.8.3 Impact of QoS/QoP on Flow

The impact of QoS or QoP on flow has not been thoroughly investigated previously. The analysis shows that QoP accounts for 11.4% of flow variation and it predicts flow significantly well ($R^2 = .114$; $F = 1.675$).

7.5.8.4 Impact of QoS/QoP on Learning

The impact of QoS on learning has been investigated in this research group, although with reduced media and without consideration of flow experience. The results of this study confirm the results and show that QoP accounts for 2.8% of learning variation. The level of significance is very low.

7.5.8.5 Impact between Flow and Learning

A strong relationship between flow and learning has been reported in the literature [148]. The results of this study confirm this with flow accounting for 15.8% of learning variation and a significant contribution, predicting flow significantly well (R^2 = .114; F =). A similar conclusion can be drawn for the impact of learning on flow, which equally accounts for 15.8% of variation in flow (R^2 = .158; F = 2.445). Although significance levels vary strongly with <.3 for prediction of the impact of learning and flow compared to a significance level of <.005 for the impact of flow on learning.

7.5.8.6 Impact of QoS/QoP on Experience

The direct impact of QoP on the experience did produce less than satisfactory results. Although the R^2 value indicates that QoP accounts for 6.5% of the experience, F <1 shows that the impact is not significant. The reason might be that the post survey captures the overall impression, which is coined by the memory of the learning and the flow experience. QoS might have interrupted the flow experience in the process of the course, but it seems that this is not pulled together by the users.

7.5.8.7 Impact of Usability on Experience

Although usability was not specifically included in the proposed model it was always recognized as contributing factor for experience and was therefore included in the measurements. In the course of the user tests this turned out to be a valuable decision. Usability accounts for 48.8% of the experience and also makes a significant contribution, predicting experience significantly well (R^2 = .488; F = 12.375).

7.5.8.8 Conclusions Post Survey

The goal of this research is to explore if and how QoS affects the Quality of Experience. The results of this study show that QoP does not significantly affect experience directly. However it affects learning and flow significantly and both factors in turn affect the experience of the learners. In addition usability turned out to be the strongest factor directly affecting experience.

With a small sample size and the language learning setting, caution must be applied, as the findings might not be transferable to any e-learning situation. They do merit further investigation though – this will be explored further in the future work section in chapter 8.

7.6 Pre-Post-Tests – Results and Analysis

The pre-test was submitted by all participants at the beginning of the course. The pre-test is an academic writing test which consisted of 12 questions and combined a mix of question techniques such as true/false, matching, multiple choice and short answers.

The post-test consisted of four tasks and assessed the knowledge about academic writing at the end of the course. The first task asked to correct a sample text with a few paragraphs for errors in structure, grammar, spelling and punctuation. The second task asked to identify which section of an article two separate paragraphs represented. The third task asked to describe characteristics of a well written paragraph and finally task four required to match text samples with the sections of an academic text. The post-test results are presented in a case study; it was given to a small sample of seven students. It was planned to give the post-test to all learners during their last sessions, but many of the learners stopped attending without prior notice. The post test was taken by seven participants; results are described with descriptive statistics.

7.6.1 Results

The pre-test average mark was 30 percent; the post-test average mark was 40 percent. The median mark in the pre-test was 30 percent, in the post-test the median mark was 40 percent. Marks in the pre-test ranged from 18 to 39 percent, while in the post-test marks ranged from 19 to 60 percent.

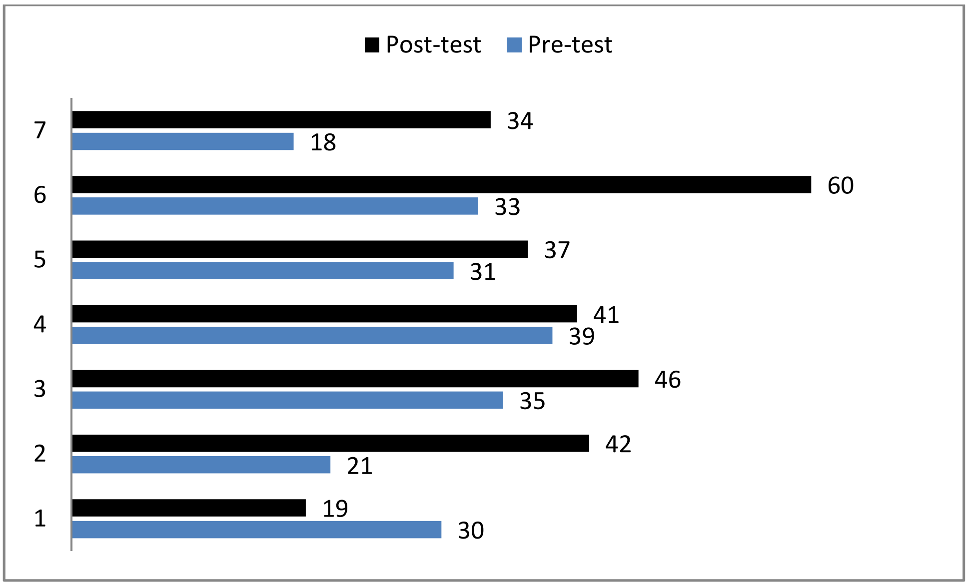

Figure 50: Results Pre-post test

The results showed that most participants had improved results in the post test. The increase in points varied and in one case the mark in the post-test was considerably lower than in the pre-test. A follow up interview with the participant with lower score in the post-test showed that the pre-test allowed more for reproduction of rote learning, while the post-test asked for application of the newly learned skills, which the participant found considerably more challenging. The participant felt more familiar with the reproduction of rote learning, based on previous learning environments. In summary the results showed that the course improved the knowledge about academic writing.

7.6.2 Dropout rates among respondents

The course seemed to confirm high drop-out rates for online learning, but on closer examination it became clear that this was a different situation. A follow-up on those participants who dropped out showed that 10 students, which is a quarter of those registered at the start, left Ireland early because of religious engagements, in particular the start of Ramadan. Another group of 9 postgraduate students found out on very short notice that their transfer reports were due a few weeks after the beginning of the course. The remaining students showed very low dropout rates for course attendance, but decreased at the end of the course which was also the end of the summer and in particular the Saturday morning group diminished. Course probing was less affected, except for the final learning assessment, which turned out to be difficult to collect. Conclusions from these results were therefore treated as case study rather than general results.

7.7 Conclusions User Testing

The user tests set out with the aim of assessing the impact of QoS on learning and flow experience. In particular the impact of adapting course material to network conditions (QAMM1) compared to adaptation to network conditions and a mix of media (QAMM2) was under investigation.

Although much attention was paid to the selection of the test environment and the recruitment of participants as well as the design of the test course, there might be an impact on the results by factors not considered. These unwanted interferences could be based in the learners, e.g. previous learning experiences and resulting preferences or their overall condition or mood on the test day. Some types of activities seemed to be more suitable and more challenging to some of the participants than others. The technical setup did not cause any major disturbances, however there might have been problems which were not reported. The quality of the content, in a technical and a learning context, is a significant factor. To filter out most possible influences of any of the related factors, the learning and technical quality was assessed by an expert. However the test course was produced in a research environment, not in a professional production setting. These limitations were considered for the following conclusions.

The most interesting finding was that QAMM2 had a significant effect on several test factors with an impact on flow and eventually on QoE, while the direct impact of QAMM2 on experience was much less. One implication of this is the possibility to improve QoE by enhancing flow with QAMM2 and thus indirectly improve QoE.

Another interesting result is that there is a functional chain of QAMM2 affecting QoP, which then affects flow, which in turn affects QoE.

The results of the user tests can be summarized in a structural model that clarifies dependencies between factors of the model and impact of the proposed algorithm QAMM2 (see Figure 51). QAMM2 affects three factors, QoP, which is the perceived QoS, flow and experience.

QoS affects learning, but only slightly. It has a medium affect on flow. Flow and learning have an equally medium effect on each other. Flow has a strong affect on experience. Learning and usability both have a very strong effect on experience. The impact percentages found in the statistical analysis are provided in Figure 51 and indicate the impact of each aspect separately. They do not consider or compare to the remaining aspects and therefore the annotations will not add up to 100%. An overall comparison adding up to a total of 100% could be done using a structural equation model, but this would require much more testing involving several hundred participants, which is beyond the scope of this research.

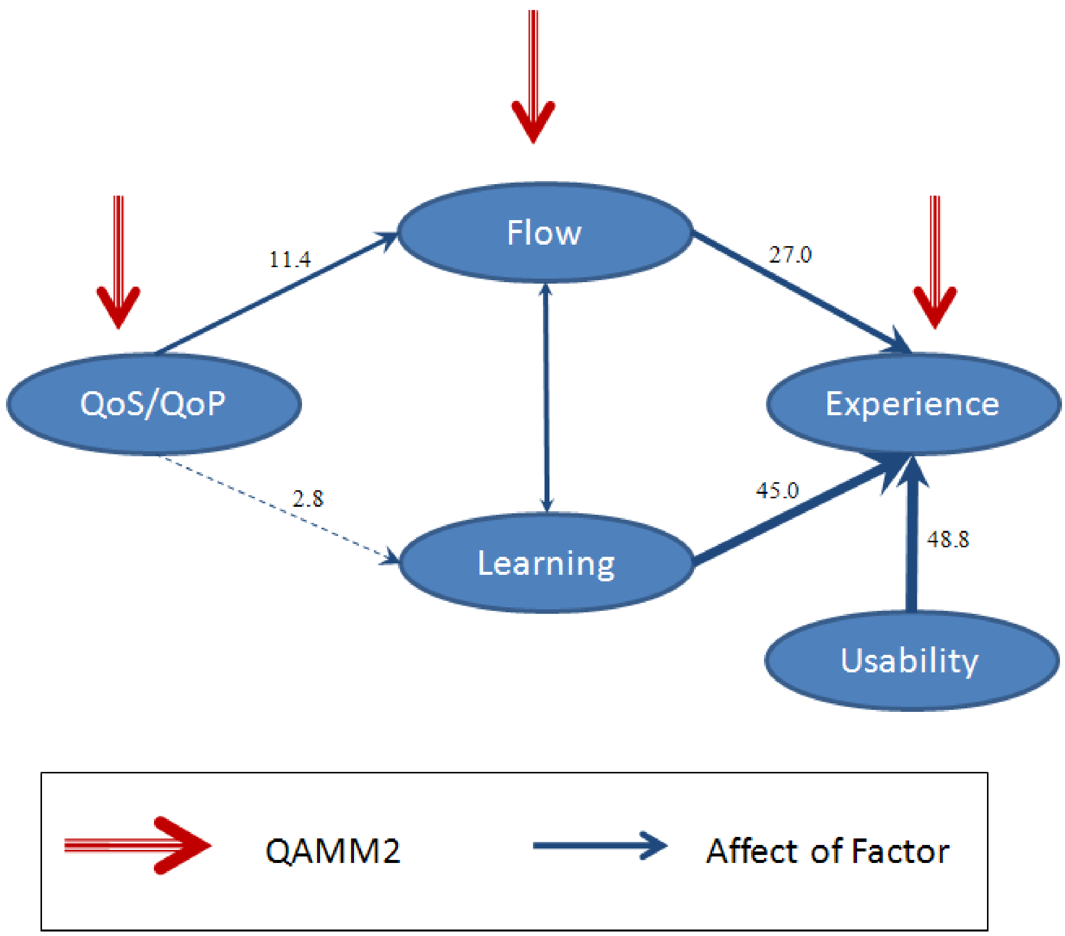

Figure 51: Summarizing Structural Model

The results of the post survey showed that usability was not good, in particular the navigation. This was rooted in the design of Moodle and it was not possible to solve this in the context of these tests. Moodle for example changes the navigation when any of its activities are used. It was initially very confusing for users to find the way back to the main course page or the respective activity page. After a few sessions the participants got used to the navigation, but still commented how inconvenient it is. The strong impact usability has emphasizes once more that Quality of Experience or user experience in multimedia e-learning can only be discussed against the background of sound basic website development, which includes consideration of usability concerns.

The results show that the combination of probing and survey is a valid combination of measurement tools and could be confirmed as measurement model. They provide an insight in an overall-state and a process measure. While for example during the course the different adaptation schemes cause an immediate response, this is softened in retrospect and for example QoP results are much more positive. Additionally the most outstanding factors, good or bad, will be reported in retrospect. The probing therefore gives feedback on what affects the learners while they are in the process of learning, while the post survey gives an insight about the factors that overall affect a decision to continue or to return to learning.

A number of issues for future research can be derived from the results. They will be included in the future work section in the final chapter.

8 Conclusions and Future Research

This chapter highlights the main conclusions from this research, presents its contributions and outlines some suggestions for future work.

8.1 Conclusions

This research aimed to find a solution to improve Quality of Experience in multimedia e-learning systems under varying network conditions. Existing multimedia e-learning systems do not consider changes in network conditions such as available bandwidth. This can cause considerable negative effects on the Quality of Experience through long startup delays and low quality of the delivered multimedia. Previous solutions aimed at adapting the media to the given network conditions. In the context of e-learning this may cause loss of information and requires extensive alterations of the media. As a solution an algorithm (QAMM2) was proposed that combines consideration of network conditions as well as learning and motivational aspects for the selection of suitable learning materials.

A. Quality of Experience in multimedia e-learning systems must be viewed in a broad sense.

Previous work on Quality of Experience in multimedia e-learning systems mainly considered objective parameters combined with usability testing. The term Quality of Experience originates from a background of technical performance. Although the definition introduced by ITU in 2007 recognizes that QoE may be influenced by user expectations and context, it does not specify this any further. The term user experience, which is rooted in the context of human-computer-interaction, explicitly recognizes the influence of emotions, enjoyment of interaction with the system and the importance of context for the experience of the user. Recognition of the context includes consideration of different roles of the person interacting with the system; in e-learning these are the roles of learner, user and customer. These roles generate different expectations each of which have to be met to create high quality experiences. The adaptation algorithm QAMM2 caters for the requirements of the learner supporting learning, more importantly by supporting flow experiences. Flow experiences have been shown to affect learning in a positive way. The user expectations regarding system performance are considered for example with a reduced startup delay. Increased enjoyment addresses the customer, who requires some added-value beyond the mere learning with the system.

The impact of Quality of Experience can only be truly measured if it is embedded in an adaptive e-learning system with an informed learning design and embedded in a larger adaptation scheme catering for knowledge level adaptation and other adaptation parameters crucial for the given context.

B. Quality of Experience in multimedia e-learning systems can be improved by adjusting the content media format to suit network conditions with the QAMM2 algorithm, combining QoS adaptation and media mix adaptation.

E-learning is plagued by high drop-out rates, often due to lack of motivation. A variety of different media are known to motivate learning. However, media diversity in e-learning systems to booster motivation can have a reverse effect if network conditions are not considered. On the other hand high quality of media transmission alone does not affect the quality of experience much. Diversity of media has to maintain good service quality. User tests showed that QAMM2 with its combination of both those aspects has a positive effect on the perceived quality of media (QoP), the flow experience and finally the quality of the experience.

C. Learning and flow experience are key contributors to Quality of Experience in multimedia e-learning systems.

Quality of Experience in multimedia e-learning systems is a fairly new and still ambiguous, but is nevertheless a highly relevant concept for the success of multimedia e-learning. The user tests showed that flow experience and learning very strongly affect the Quality of the Experience. Among the factors in the QoE model also affected by Quality of Service, learning was the factor with the strongest immediate impact on Quality of Experience, while flow experience was found to be the second strongest factor with a direct impact. The Quality of Experience model proposed initially could therefore be confirmed – within the limitations for individual parameters' effects on Quality of Experience as outlined above.

This has strong implications for future adaptive multimedia e-learning systems. Existing multimedia systems can improve their quality of experience or, expressed in marketing terms, their product quality by adding the proposed algorithm to their system - provided a system has a high level of learning design quality. The improvement of the Quality of Experience is especially relevant for learning systems that rely on customer perceived quality, motivation and engagement of the learner, as circumstantiated by the results of the user testing.

D. **Not only is flow experience crucial to QoE, but it is the main conduit through which QoS impacts QoE.**

This research looked at the different relationships of flow experience in multimedia e-learning and found that it is highly relevant for Quality of Experience. Flow experience has very strong ties with all connected factors.

Most prominent is the strong impact of flow experience on the quality of experience. Furthermore flow experience is strengthened significantly by the proposed QAMM2 algorithm, in particular through an improvement of enjoyment and an increase in time distortion. In addition flow is affected by the perceived quality of Service (QoP); almost equally strong as the impact of flow on learning. The research confirmed the impact of flow experience on learning and an equally strong impact of learning on flow experience.

E. **The impact of the QAMM2 algorithm on Quality of Experience varies between short-term impact and long-term impact.**

The course probing demonstrated a significant impact of QAMM2 on Quality of Experience, while the post survey did not confirm an immediate impact of Quality of Perception on the Quality of Experience. This shows that the perception of the learner changes over time. An explanation might be that during the course a lack of sufficient network resources prevents access to the predominant activity (learning) and interrupts the focus of attention. In retrospect the learner has a broader perspective on the course, including for example the suitability of the learning material or the learning environment, and the impact of the network conditions and the media mix is obscured.

F. **The impact of Quality of Service on Quality of Experience in multimedia e-learning has been under-estimated and deserves more consideration.**

The Delphi study at the beginning of the research showed that QoS-related adaptation is not considered of high relevance. The experts ranked the hypotheses relating to QoS very low. Yet the comments regarding agreement with those hypotheses showed that much of the low rankings expressed a tentativeness, because of a lack of available research results or a lack of own research in this area. However, the results of this research show that there is significant positive impact of the QAMM2 algorithm, which combines consideration of network conditions and media mix, on Quality of Experience.

8.2 Summary of Contributions

The main contributions of this thesis are a model and adaptation policies for Quality of Experience in multimedia e-learning and an associated measurement model.

A. **Model for Quality of Experience in multimedia e-learning**

The model combines five relationships between four variables of Quality of Experience. The four variables are Quality of Service (QoS), flow experience, learning and Quality of Experience.

Of these variables Quality of Service, flow experience and Quality of Experience are significantly affected by the proposed QAMM2 algorithm.

The first two relationships connect QoS with flow and learning.

- QoS impacts learning.
- QoS impacts flow experience.

There is a strong relationship between QoS and flow experience, while the relationship between QoS and learning is considerably weaker, but within the limits of statistical significance.

Next is the mutual relationship between flow and learning. These two factors significantly affect one another equally.

The last two relationships are between learning, flow experience and Quality of Experience.

- Flow experience impacts Quality of Experience.

- Learning impacts Quality of Experience

The impact of both factors is strongly significant. Learning has the strongest direct impact on Quality of Experience of all contributing factors, followed by flow experience.

B. Adaptation policies for Quality of Experience in multimedia e-learning

There are two adaptation polices combined into an adaptation strategy. The first policy selects media formats suitable to given network conditions. The second policy decides which media format to deliver based on the media history, avoiding the media format that has been delivered immediately before unless the network conditions do not allow for any variation.

C. Measurement model for Quality of Experience in multimedia e-learning

None of the factors in the QoE model can be observed directly. Therefore indicator variables have to be measured. The measurement model outlines the factors of the QoE model and their respective indicators.

Indicators for flow experience are time distortion and immersion. Learning indicators are qualitative pre-post tests, quantitative achievement and the learning activity. Network conditions are indicated by available bandwidth and media mix is characterized by media distribution.

Measuring Quality of Experience with the measurement model provides a reliable monitor for the impact of the adaptation policies.

8.3 Future Work

A. Accessibility-based Software Engineering Framework for User Experience across Multiple Devices

The web has evolved from a pure content presentation medium into a platform for rich interactions and collaborative activities. However, in many cases web accessibility and cross device user experience has not kept up with these developments. The lack of continuous comparable user experience creates digital exclusion. With a growing number of essential everyday services provided via the internet (online tax, citizen information, education etc) this is more than an inconvenience, but a matter of exclusion of large numbers of users and the so-called “digital divide” is seen as a problem by many governments. The lack of suitable tools to integrate user experience in the work flow makes it complicated to maintain user experience across a variety of learners and devices.

Based on the work in this thesis, this line of work aims to design and test a software engineering framework for creating and describing interactive content that has a guaranteed level of web accessibility while providing an equivalent user experience across multiple devices and usage contexts.

The framework will comprise a process model, work flow recommendations, interaction models, metrics for the combined process and best practices. The framework will integrate with related software engineering process models (e.g. [191] [209] [199] [219]) and previous accessibility research (e.g. [207]), but unlike those it will focus on quality of user experience.

By testing and applying proposed process models in real project situations, it is hoped that a realistic model and workflow will emerge that can be easily adapted by companies producing online user experiences. Ideally the process that emerges will address platform independence and address ways to optimise the user experience across current and future platforms.

B. Structural Equation Modelling

The results of this thesis show that a broad view on factors affecting Quality of Experience is necessary. To explore the concept of Quality of Experience further it is necessary to identify a method to balance a growing number of variables. Often these variables are latent, meaning they cannot be directly observed. Structural Equation Modelling [187] has been used in research on flow in computer-mediated environments [195] [167], flow in online games [28] and education [198] to analyse multidimensional constructs.

Structural Equation Modelling (SEM) enables to use multiple observed variables, while basic statistical methods only use a limited number of variables. Additionally SEM allows including measurement error in the statistical analysis; this increases validity and reliability of the results. SEM analysis aims to determine how a theoretical model is supported by different variables. SEM uses hypothesis testing to develop a better understanding of the relationships among constructs the model is made of and their relationships. An SEM model has two main components, the measurement and the structural model. The measurement model defines the relations between observed and unobserved variables, while the structural model defines the relations among the unobserved variables only.

The SEM approach is considered a promising route for future work and collaboration to investigate an increasingly comprehensive bundle of factors affecting Quality of Experience in multimedia e-learning.

C. User experience in Multimedia e-Learning

Further research could explore the impact of additional factors on QoE and how these factors are affected by the proposed algorithm. Another important issue for future research is how to add information about flow to the proposed algorithm and adjust the adaptation accordingly.

In interviews following the post survey users acknowledged that the course helped them to gain knowledge, but they did not feel able to apply it better. A suggestion from the participants to change this was to provide detailed individual feedback on assignments and more individual interaction with the tutor. This seems a suitable solution, although not feasible within the user tests for this research. It showed though that the course was not perceived as an artificial situation, but a real life learning setting. This presents the issue of combining QoS-based research on QoE in multimedia e-learning with research on blended learning. In this combination QoE would undeniably have to be embedded in the slightly broader concept of user experience.

The measurements for this research could partially be automated, based on the existing measurement model. Time distortion could be measured by comparing the minimum numbers of units to the actual units done. An analysis of the server logs could provide the necessary data. Immersion could be measured by providing light distractions - usage monitoring will show whether the learners react to the distractions. Bandwidth could be estimated automatically and feed directly into the adaptation algorithm. The flowplayer [66] and the SMIL-compatible ambulant player [17] provide mechanisms to adapt the type of media played to available bandwidth. The media mix can be monitored by using the log files for each user and can be implemented using SMIL [45]. The automatic assessment of the learner's knowledge level has been implemented in several adaptive systems [16].

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Appendices

Appendix A –

Delphi Advisor Panel Documents & Delphi Invitation

1 Interview Guidelines

A Learner, is a Learner, is a User, is a Customer

- So what exactly do you mean by Quality of Experience?

An e-learner's Quality of Experience (QoE) is informed by previous experiences as a learner, a user of computer/web-based systems, and a customer. We propose a holistic view on QoE, considering the different roles of the learner as learner, user and customer, that has been missing until recently. A number of factors have been identified that are likely to impact on QoE.

The adaptation of our system aims at a good QoE. Flow-related as well as learning-related aspects are the main components of the QoE, which are both influenced by quality of service (QoS).

This Delphi study explores an initial ranking of the importance of these factors.

The panel for this Delphi study consists of experts from research in the area of e-learning, e-commerce, adaptive systems, and psychology. The study also includes experts from the e-learning industry and e-learners, although learners will be involved mainly while developing the prototype and during user testing of the prototype.

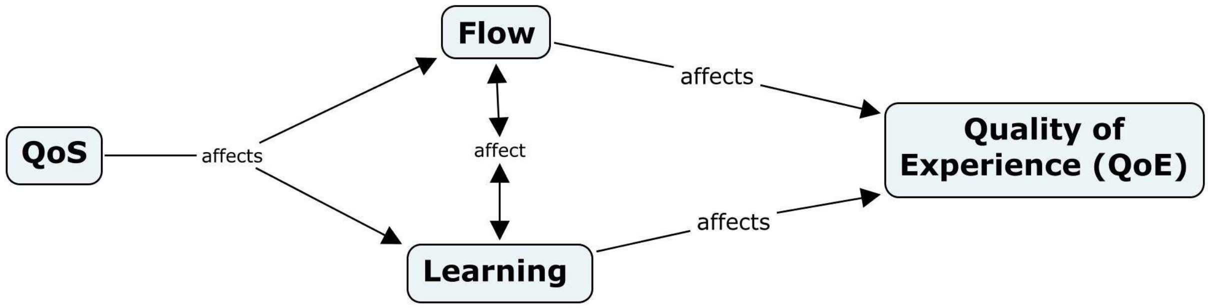

Figure 52: QoE Model

Flow

The concept of flow was first introduced by Csikszentmihalyi and it represents the optimal experience or complete absorption with an activity. It is characterized by 8 dimensions, which can be divided into three stages: antecedents, experiences and effects. The dimensions allocated to the antecedent stage are a clear set of goals, immediate feedback and equilibrium between challenges and skills. The experience stage is characterized by the merging of action and awareness, focused concentration and a sense potential control. The final effects stage is characterized by a loss of self-consciousness, time distortion and a self-rewarding experience. Flow has also been described as a match between skills and challenges, and depending on the match or mismatch, it results in flow, boredom or anxiety.

Learning

Learning is characterized by learning and teaching methods, learning styles, different learning theories, the quality of feedback and interaction influence as well as the ratio of skills and challenges.

QoS

The interdependence of network-level parameters and media type defines the relevance of the QoS elements. Delay, jitter and loss can be highly disadvantageous for the QoE, but they can also enhance the QoE. For example a video-based presentation can have a better QoE, if the loss of frames keeps some pictures longer available while the audio information continues, because it provides more time to take in the visual information.

Figure 53: ISO e-learning

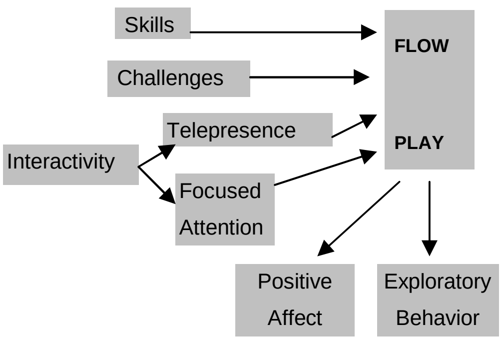

Figure 54: Flow dimensions

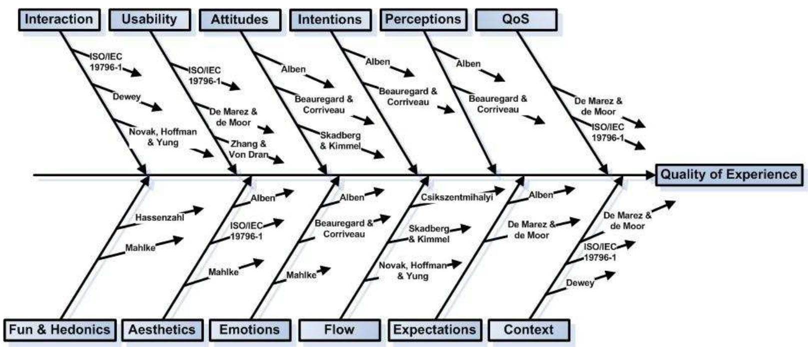

Figure 55: Aspects of QoE

FLOW

Hypothesis 1: Increased attractiveness of a learning environment enhances flow.

[18] found a strong correlation between attractiveness of a website and flow experiences. The level of enjoyment of a website depends on the media presentation and whether it supports the user in understanding the content of the website easily [24]. The concept of 'technology as a toy' [25] describes how a well-designed technology interface can be intrinsically motivating for the user.

Hypothesis 2: A balanced skill and challenge ratio enhances flow.

Flow has been described as a match between skills and challenges, and depending on the match or mismatch, it results in flow, boredom or anxiety [26].

Hypothesis 3: A clear set of goals corresponds to improved flow.

[15] defines a clear set of goals and fast feedback as two dimensions of flow.

Hypothesis 4: Good interactivity of a learning environment corresponds with a focus of attention on the activities in the learning environment.

Interactivity is a way to increase the telepresence, a state where the user is more aware of things in the virtual world than in his or her physical surroundings [16].

Hypothesis 5: Better ease of use of the learning environment corresponds with improved interactivity.

If the user can find relevant information easily, interaction with the system becomes quicker and more enjoyable and motivates the user to interact longer with the system [18].

Hypothesis 6: Better ease of use of the learning environment corresponds with clearer focus of attention

Hypotheses 7: Improvement of QoS when delivering various multimedia types can improve the flow experience.

The interdependence of network-level parameters and media type defines the relevance of the QoS elements. Delay, jitter and loss can be highly disadvantageous for the QoE, but they can also enhance the QoE. For example a video-based presentation can have a better QoE, if the loss of frames keeps some pictures longer available while the audio information continues, because it provides more time to take in the visual information [24], [28], [27].

Hypothesis 8: An increase or decrease of the resolution of multimedia leads to increase or decrease in learning.

Hypothesis 9: A more intense flow corresponds with improved learning results.

Users experiencing flow are more likely to also show improved learning results [18].

LEARNING

Hypothesis 10: Applying conversation style texts leads to a more personalized learning environment and corresponds with more intense learning for beginners.

In a study on multimedia learning it could be shown that applying more conversational language and combining different media makes it easier for the learner to accept that they are in a human-to-human interaction and this leads to an effort of the learner to understand what the other person is saying, which leads to more intense learning [28].

Hypothesis 11: Reduction of videos to selected images (frames) can increase learning if the auditory narration quality is maintained.

Hypothesis 12: An increase or decrease of the resolution of multimedia leads to increase or decrease of flow.

Education research shows [28] that a reduced number of images in educational materials actually improve the learning due to the fact that all information processing channels have a limited capacity. This also explains why materials addressing different processing channels (for example audio and visual channels) result in better learning. Similarly, research on the Quality of Perception and QoS found that a significant loss of frames in videos improves the learning outcome [29].

Hypothesis 13: Learning materials with a mix of animation and on-screen text leads to more intense learning.

The concept of multimedia learning is based on a learning model which assumes that learning is best when it combines verbal and visual information [28].

Hypothesis 14: A balanced skill and challenge ratio corresponds with increased learning.

Flow experiences are often related to tasks that match the skill level of the learner and the mastery of the challenges can promote feelings of self-confidence [25] or self-efficacy which will then lead to a better motivation to learn. [30]. Challenges as well as skill only have a weak impact on the flow whereas both factors had a considerable affect on the learning intensity [18].

Hypothesis 15: A clear set of goals corresponds to improved learning.

A clear set of goals has been identified as an antecedent of flow by [31] and [32] point out that andragogical learning is always goal-focused and strives to enable the learner to face challenges in everyday life.

Hypothesis 16: Faster system feedback about progress corresponds with more intense learning.

The speed of the system feedback has a direct impact on the learner's approach to challenges. The faster a system reacts, the more likely that the flow experience is not interrupted and the learning does not loose its intensity [18].

Hypothesis 17: Increased choice between a set learning path and free activity improves learning results.

A lack of autonomy in selecting the learning path leads to frustration and has a negative impact on the flow experience [33].

Hypothesis 18: The sequence of the multimedia mix (text, video versus video, text) affects learning.

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2 Invitation Delphi Study

A Learner, is a Learner, is a User, is a Customer -

So what exactly do you mean by Quality of Experience?

Invitation / Panel Profile

Dublin, 19 March 2009

Dear Sir / Madam,

The research project PAMAH investigates different aspects of adaptive hypermedia e-learning systems and in particular the Quality of Experience of the learner. Initially we investigate aspects that have an impact on the Quality of Experience in e-learning. I would be grateful for your participation in the Delphi study.

The study will include experts who are immediately concerned with the topic and can bring different perspectives to the study. The Delphi study collects feedback from selected experts and has three (on line) rounds **between March and June 2009**.
The first round collects initial feedback to a number of hypotheses and some general information from the participants (see below).
The second round gives back hypotheses to the participants where no consensus among the expert panel was found, and additional comments given by the participants. It asks again for your feedback. In this round you will also receive information, which hypotheses got a consistent evaluation from the majority of the experts.
The third round will be necessary in case there are still very diverse opinions on any of the hypotheses.

The **first round of the study** consists of 3 parts.
Part I asks for details of the participants; mainly area of expertise and contact details. We will not publish any individual results and only the researcher conducting the study (Sabine Moebs) will have access to those details. We require the information to conduct the different rounds of the study,
Part II is the actual Delphi study. In the first round an online questionnaire requires evaluation of a number of statements derived from recent research. The evaluation of all participants of the Delphi panel is summarized and given back to the panel for a second evaluation. In case that after the second round there are still questions with very different evaluations across the panel, these statements are given back to the panel again.
Part III provides some information on your own experience with learning technologies and asks for your feedback regarding their role in future learning systems.

The study combines expertise from these groups:

- Researchers from the areas of e-learning, adaptive systems and multimedia engineering or related areas.
- Trainers and providers of e-learning

Requirements for participation

- Research activities and publications in the area of e-learning, adaptive systems and multimedia engineering or related areas.
- Trainer or provider in/of e-learning programs
- Internet access

Participation

- Fill out the 3 online questionnaires, available between the **middle of March and the end of June 2009** (estimated time is 3x30 min.) using the link to the study provided in the email.

Please do not hesitate to contact me if you have any questions concerning the study.

Best regards from Dublin

Sabine Mőbs

Dublin City University, Performance Engineering Lab, Glasnevin, Dublin

sabine@eeng.dcu.ie **|** skype:sam4223 **|** +353 1 700-7644

Appendix B - User Test Documents

1 Felder Learning Styles Questionnaire

NC STATE UNIVERSITY

Index of Learning Styles Questionnaire

Barbara A. Soloman
First-Year College
North Carolina State University

Richard M. Felder
Department of Chemical Engineering
North Carolina State University
Raleigh, North Carolina 27695

Directions
Please provide us with your full name. Your name will be printed on the information that is returned to you.
Full Name
For each of the 44 questions below select either "a" or "b" to indicate your answer. Please choose only one answer for each question. If both "a" and "b" seem to apply to you, choose the one that applies more frequently. When you are finished selecting answers to each question please select the submit button at the end of the form.

I understand something better after I
(a) try it out.
(b) think it through.

I would rather be considered
(a) realistic.
(b) innovative.

When I think about what I did yesterday, I am most likely to get
(a) a picture.
(b) words.

I tend to
(a) understand details of a subject but may be fuzzy about its overall structure.
(b) understand the overall structure but may be fuzzy about details.

When I am learning something 5. new, it helps me to
(a) talk about it.
(b) think about it.
If I were a teacher, I would rather teach a course
(a) that deals with facts and real life situations.
(b) that deals with ideas and theories.

I prefer to get new information in
(a) pictures, diagrams, graphs, or maps.
(b) written directions or verbal information.

Once I understand
(a) all the parts, I understand the whole thing.
(b) the whole thing, I see how the parts fit.

In a study group working on difficult material, I am more likely to
(a) jump in and contribute ideas.
(b) sit back and listen.

I find it easier
(a) to learn facts.
(b) to learn concepts.

In a book with lots of pictures and charts, I am likely to
(a) look over the pictures and charts carefully.
(b) focus on the written text.

When I solve math problems
(a) I usually work my way to the solutions one step at a time.
(b) I often just see the solutions but then have to struggle to figure out the steps to get to them.

In classes I have taken
(a) I have usually gotten to know many of the students.
(b) I have rarely gotten to know many of the students.

In reading nonfiction, I prefer
(a) something that teaches me new facts or tells me how to do something.
(b) something that gives me new ideas to think about.

I like teachers
(a) who put a lot of diagrams on the board.
(b) who spend a lot of time explaining.

When I'm analyzing a story or a novel
(a) I think of the incidents and try to put them together to figure out the themes.
(b) I just know what the themes are when I finish reading and then I have to go back and find the incidents that demonstrate them.

When I start a homework problem, I am more likely to
(a) start working on the solution immediately.
(b) try to fully understand the problem first.

I prefer the idea of
(a) certainty.
(b) theory.

I remember best
(a) what I see.
(b) what I hear.

It is more important to me that an instructor
(a) lay out the material in clear sequential steps.
(b) give me an overall picture and relate the material to other subjects.

I prefer to study
(a) in a study group.
(b) alone.

I am more likely to be considered
(a) careful about the details of my work.
(b) creative about how to do my work.

When I get directions to a new place, I prefer
(a) a map.
(b) written instructions.

I learn
(a) at a fairly regular pace. If I study hard, I'll "get it."
(b) in fits and starts. I'll be totally confused and then suddenly it all "clicks."

I would rather first
(a) try things out.
(b) think about how I'm going to do it.

When I am reading for enjoyment, I like writers to
(a) clearly say what they mean.
(b) say things in creative, interesting ways.

When I see a diagram or sketch in class, I am most likely to remember
(a) the picture.
(b) what the instructor said about it.

When considering a body of information, I am more likely to
(a) focus on details and miss the big picture.
(b) try to understand the big picture before getting into the details.

I more easily remember
(a) something I have done.
(b) something I have thought a lot about.

When I have to perform a task, I prefer to
(a) master one way of doing it.
(b) come up with new ways of doing it.

When someone is showing me data, I prefer
(a) charts or graphs.
(b) text summarizing the results.

When writing a paper, I am more likely to
(a) work on (think about or write) the beginning of the paper and progress forward.
(b) work on (think about or write) different parts of the paper and then order them.

When I have to work on a group project, I first want to
(a) have "group brainstorming" where everyone contributes ideas.
(b) brainstorm individually and then come together as a group to compare ideas.

I consider it higher praise to call someone
(a) sensible.
(b) imaginative.

When I meet people at a party, I am more likely to remember
(a) what they looked like.
(b) what they said about themselves.

When I am learning a new subject, I prefer to
(a) stay focused on that subject, learning as much about it as I can.
(b) try to make connections between that subject and related subjects.

I am more likely to be considered
(a) outgoing.
(b) reserved.

I prefer courses that emphasize
(a) concrete material (facts, data).
(b) abstract material (concepts, theories).

For entertainment, I would rather
(a) watch television.
(b) read a book.

Some teachers start their lectures with an outline of what they will cover. Such outlines are
(a) somewhat helpful to me.
(b) very helpful to me.

The idea of doing homework in groups, with one grade for the entire group,
(a) appeals to me.
(b) does not appeal to me.

When I am doing long calculations,
(a) I tend to repeat all my steps and check my work carefully.
(b) I find checking my work tiresome and have to force myself to do it.

I tend to picture places I have been
(a) easily and fairly accurately.
(b) with difficulty and without much detail.

When solving problems in a group, I would be more likely to
(a) think of the steps in the solution process.
(b) think of possible consequences or applications of the solution in a wide range of areas.

2 Participant Profile

Minimum
Attendance
2 Units

Letter of Consent / Panel Profile

Dear participants,

I am inviting you to participate in a research project to study user experience in multimedia e-learning. To make this as beneficial to you as possible this English course has been developed in cooperation with DCULS. Along with this letter is a short questionnaire that asks a small number of questions about demographics and your technical background.

Please fill it in and give it back to me before continuing with the first session.

The results of this project are part of my PhD research. Through your participation I hope to understand the impact of the technical environment on multimedia e-learning. I hope that the results of the survey will be useful for research into accessibility of learning environments and I hope to share my results by publishing them in a dedicated scientific journal. The pilot study will also be used to develop a course for future (research) students and it is planned to make it available on the web.
I do not know of any risks to you if you decide to participate in this survey and I guarantee that your responses will not be identified with you personally.

I promise not to share any information that identifies you with anyone outside my research group which consists of me and my supervisor Dr. Jennifer McManis. I will be the only one handling user-related data.

There are no risks to you or to your privacy if you decide to join my study by filling out this survey. But if you choose not to participate that is fine. Even if you decide not to participate I would be very happy to share my results with you if you are interested. To get a copy of my results check my micro-blog at twitter.com/sabine_dcu .

If you agree with the above, please fill in and sign the questionnaire.

Best regards
Sabine Moebs

3 LUCie Questionnaire

Please fill in the answers to the questions and sign below.

First name **Last name**

Age (please circle one of the options)

20-25	26-30	
31-35	36-40	
41-45	46-50	>50

Nationality

Sex (please circle one of the options)

m f

Level of Education (please circle your highest educational level)

BSc or BA / MA / MSc / PhD
Other:

Study area (please circle all matching options)

Business	Science
Technology	Languages
Education	Other:

Language study (How long have you been studying English?)

year(s) month(s)
Please include all English classes in school, at university or elsewhere.

Language qualification (TOEFL, translator exams, IELTS, etc)

Time spent in English speaking countries (1 month and more at a time)

year(s) month(s)
Please provide the time in total spent in English-speaking countries (where English is the 1st language spoken).

e-learning experience (please circle one of the options)

once twice several times

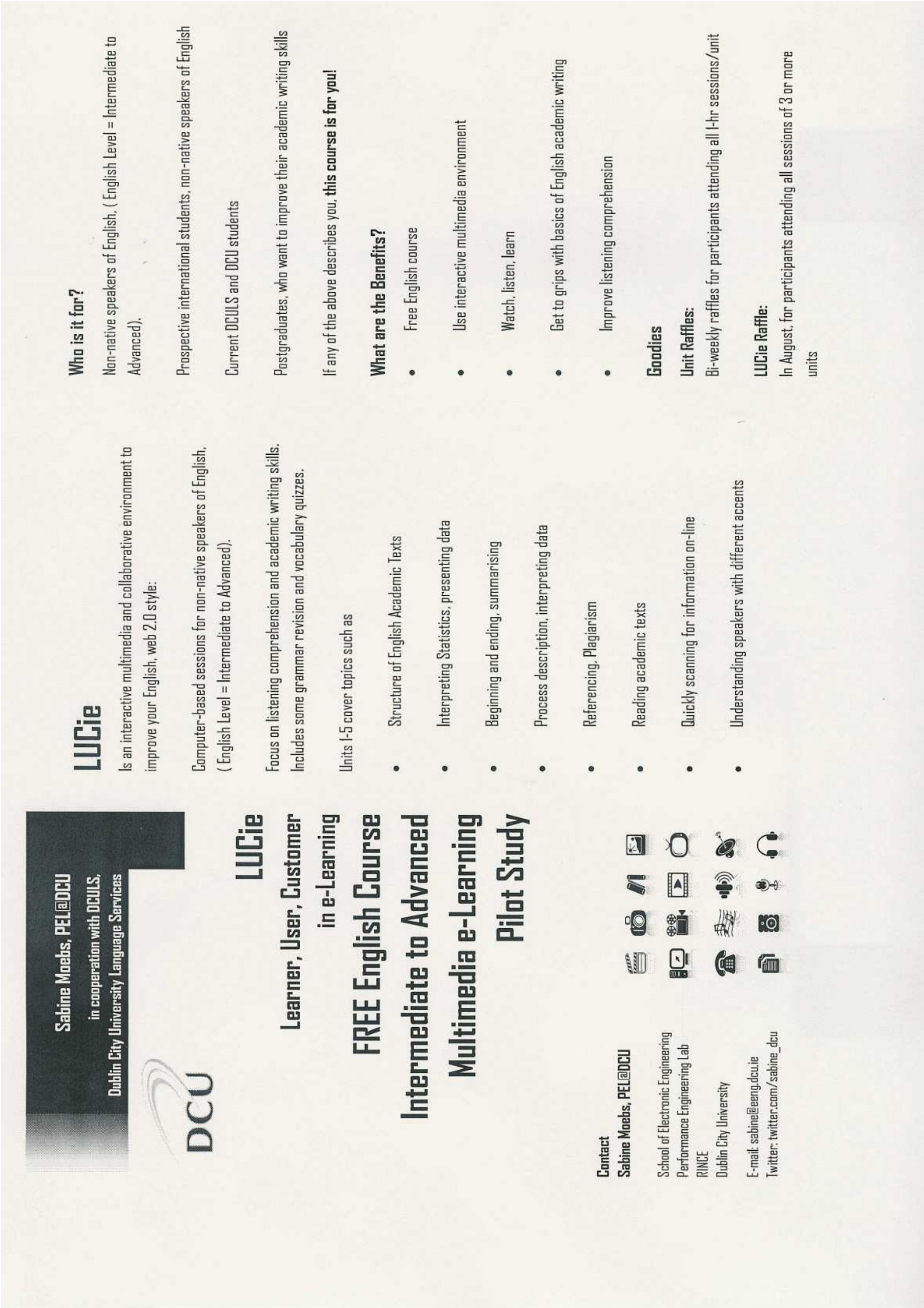
Select programs you can use easily (please circle all the options matching your skills)

Word	Excel	Access
Freemind	email program	Skype
Wiki	Blog	online forms
Chat	Elluminate	Photoshop
Eclipse	Captivate	Twitter

Date **Signature**

Name (BLOCK LETTERS)

4 LUCie Flyer



Sabine Moebs, PEL@DCU
in cooperation with DCULS,
Dublin City University Language Services

DCU

LUCie
Learner, User, Customer
in e-Learning
FREE English Course
Intermediate to Advanced
Multimedia e-Learning
Pilot Study

Contact
Sabine Moebs, PEL@DCU

School of Electronic Engineering
Performance Engineering Lab
RINCE
Dublin City University

E-mail: sabine@eeng.dcu.ie
Twitter: twitter.com/sabine_dcu

LUCie

Is an interactive multimedia and collaborative environment to improve your English, web 2.0 style:

Computer-based sessions for non-native speakers of English, (English Level = Intermediate to Advanced).

Focus on listening comprehension and academic writing skills. Includes some grammar revision and vocabulary quizzes.

Units 1-5 cover topics such as

- Structure of English Academic Texts
- Interpreting Statistics, presenting data
- Beginning and ending, summarising
- Process description, interpreting data
- Referencing, Plagiarism
- Reading academic texts
- Quickly scanning for information on-line
- Understanding speakers with different accents

Who is it for?

Non-native speakers of English, (English Level = Intermediate to Advanced).

Prospective international students, non-native speakers of English

Current DCULS and DCU students

Postgraduates, who want to improve their academic writing skills

If any of the above describes you, **this course is for you!**

What are the Benefits?

- Free English course
- Use interactive multimedia environment
- Watch, listen, learn
- Get to grips with basics of English academic writing
- Improve listening comprehension

Goodies

Unit Raffles:
Bi-weekly raffles for participants attending all 1-hr sessions/unit

LUCie Raffle:
In August, for participants attending all sessions of 3 or more units

LUCie Details

Where and When

Engineering & Research Building
Dublin City University

1 hour sessions: Monday & Wednesday afternoon
OR
2 hour sessions: Saturday morning

Optional: Additional sessions depending on demand

Dates (TBC):
Unit 1 Mon 31/05/10 - Wed 09/06/10
Unit 2 Mon 21/06/10 - Wed 30/06/10
Unit 3 Mon 12/07/10 - Wed 21/07/10
Unit 4 Wed 04/08/10 - Wed 11/08/10
Unit 5 Mon 23/08/10 - Wed 1/09/10

Sign up for Unit 1 until or before **Friday 28 May**

Sign up for all other units until the week before it starts.
Places are limited. First come, first served ;)

More Details

Pilot Course is **free.**
Participants are asked to sign up for 2-3 units
Each unit: two 1-hour sessions / week for 2 weeks

If you cannot make it to the pilot (June-August 2010):
Course will be available on-line from the end of the year (2010)
Check twitter.com/sabine_dcu for details

Cost:
*** free during pilot study***
10€ donation for each unit (4 * 1 hr)
for one of our supported charities
(after end of pilot study August 2010 only)

Next Steps

- Get in touch (sabine@eeng.dcu.ie) and sign up
- Get your account details
- Attend the sessions
- Improve your English
- Enter the unit raffles
- Attend 3 or more units to enter the **LUCie** raffle at the end of the pilot study.

DCU

Contact
Sabine Moebs, PEL@DCU
School of Electronic Engineering
Performance Engineering Lab
RINCE
Dublin City University
E-mail: sabine@eeng.dcu.ie
Twitter: twitter.com/sabine_dcu

5 Sample Lesson Outline

LUCie - Academic Writing

Jump to...

LUCie ▶ AcadWriting ▶ Resources ▶ Sat Lesson 1 Update this Resource

LUCie Saturday Sessions - Unit 1

Today's lesson will get you started and take you on a little tour around the LUCie system. You will get to know one of the tools and do a number of initial assessments.

TIP 1: On the top of the page you can see this path: **LUCie ▶ AcadWriting ▶ Resources ▶ Saturday Lesson 1**
Clicking on **AcadWriting** brings you back to the main course page.

TIP 2: If you **open any link with a right-click**, you can open that page in a new tab or a new window. This means you can for example always **keep this lesson outline open** and check easily what to do next or read the HowTo again. ☺

Please work through the following tasks (see short explanation for each below). **Please make sure you submit both assessments and the LUCie feedback as your final task.** Other than that you can work through the tasks in your preferred order.

1. English Assessment
2. Mind-mapping with Freemind
3. Academic Writing Assessment
4. LUCie Feedback

I provide a rough time estimate for each task just for your orientation - feel free to vary.

Task 1: English Assessment (20 minutes)

The first assessment is based on the placement tests typically used by DCULS. You will get a similar test during your final LUCie session.
You will have one attempt only. The first questions should be a breeze, with the difficulty level continuously increasing slightly.
Go to the main **Academic Writing** page (AcadWriting link), look up the Assessment section and right-click on 'English Assessment (1)'.

Task 2: Mind-mapping with Freemind (20 minutes)

Create a mindmap summarizing the main ideas presented in Resource 1.2 and save it to the desktop.
When you save the mindmap **include your name** in the file name.
Finally also save the mindmap as an image - again to the desktop and then upload the image in the assignment section.

First go to **Resource 1.2**.
A window with a link to Resource 1.2 will open. **Click on the link** and watch the video.
Next use **FreeMind** to create the mindmap. To open the FreeMind program click on the butterfly icon on your desktop or in the program list.
Also see the little Freemind HowTo below.

Do you know what mind mapping is? If you haven't heard about mind mapping before, wikipedia provides a good introduction. At the FreeMind website you can also look at a few examples.

We will use the mind mapping tool throughout the course and it can be a very helpful tool for the start of writing a paper or a thesis.

Quick HowTo for Freemind:

- To start FreeMind just click on the butterfly icon in the program list or on the desktop. Wait for the program to start. If you get an error message - click on "Ok" and continue.
- To open a new file go to the file menu and select "New".
- Now you will see a greyed out oval in the middle of the window. Click into the oval and write your topic in the middle.
- To **add more branches**, stay in one of the branches (they need to have a grey background) and then hit the **"insert" key on your keyboard**.

Explore the program:

- What can you do when you right click on a grey branch with the mouse?
- Try out what you can do with the different icons on the left.
- Don't forget to save your mindmap to the desktop.

Here is how to save your mindmap as an image:

- Go to the file menu
- select 'Export' and then 'As JPEG..'
- Save the jpeg with the same name as your mindmap.

Task 3: Academic Writing Assessment (15 minutes)

Please do the **Academic Writing Assessment (1)**. Don't forget to "Save without submitting" during the test and to finally "Submit and Finish".

Go to the main **Academic Writing** page (AcadWriting link), look up the Assignment section and right-click on 'Academic Writing Assessment (1)'.

Task 4: LUCie Feedback (10 minutes)

There - almost done. Just one last thing to do: Feedback for this first session. You will need a **password**; it is **"LUCie1"**.
Right-click on survey to open it in a new tab or window and submit your feedback for LUCie Unit 1.

When you are done with everything, don't forget to log out...

Last modified: Wednesday, 14 July 2010, 11:24 AM

Moodle Docs for this page

You are logged in as Sabine Moebs (Logout)

AcadWriting

6 Unit Survey Probing

1. LUCie Unit 2 - General Feedback

As you know the course is free, because it is part of my PhD research. Therefore I need your feedback at the end of each unit.

This part of the course is essential for my work. Please give me your honest feedback (rain or shine;)).

Thank you for your cooperation!

*** 1. Please enter your first and last name:**

*** 2. The following are all statements regarding the sessions during Unit 2. Please select the rating for each statement.**

	Fully Agree	Agree	Not sure	Slightly disagree	Disagree
The mix of different activities during this unit supports my learning.	○	○	○	○	○
Using the LUCie website for the first time is easy.	○	○	○	○	○
The lessons are challenging, but suitable for my knowledge level.	○	○	○	○	○
The quality of the podcast in this unit was good.	○	○	○	○	○

2. LUCie Unit 2 - Experience Feedback

Looking back at what you have learned so far, the tools you were introduced to and the tasks you had to do, please rate unit 2.

*** 1. **

	Very good	Good	A bit of both	Bad
My overall experience with this unit was	○	○	○	○

*** 2. **

	Fully	Mostly	More or less	Not at all
The unit met my expectations	○	○	○	○

*** 3. **

	Each session	Often	Sometimes	Never
Did you often loose track of time and were surprised that the session was over already?	○	○	○	○

3. Thank you! And see you soon?

Thank you for attending the sessions of Unit 2.
Please indicate below if you are planning to attend Unit 3, 4 or 5.

1. Any comments?
Three things you liked best?
Three suggestions for improvement?

7 Post Survey

Final Assessment LUCie, Part II Fall 2010 Name:

I strongly **agree** I strongly **disagree**

1. Overall, I enjoyed LUCie.
☐ ☐ ☐ ☐
2. The web site speed is fast.
☐ ☐ ☐ ☐
3. There is little waiting time for the web pages to load.
☐ ☐ ☐ ☐
4. The course is interesting.
☐ ☐ ☐ ☐
5. The design of the course is attractive.
☐ ☐ ☐ ☐
6. I had no problem finding what I wanted.
☐ ☐ ☐ ☐
7. Navigation of the course was simple and easy.
☐ ☐ ☐ ☐
8. The course provided some information that is new to me.
☐ ☐ ☐ ☐
9. I consider myself to be a knowledgeable academic writer.
☐ ☐ ☐ ☐
10. I know a lot about academic writing.
☐ ☐ ☐ ☐
11. I felt that I had the freedom to go anywhere in the web site.
☐ ☐ ☐ ☐
12. I felt efficient when I was using the web site.
☐ ☐ ☐ ☐
13. The web site's response to my actions (such as clicking a link) was fast.
☐ ☐ ☐ ☐
14. While I was browsing the course pages, time seemed to go by very quickly.
☐ ☐ ☐ ☐
15. While browsing this course, I was not aware of my immediate surroundings.
☐ ☐ ☐ ☐
16. I felt that I was in the world created by the course web site.
☐ ☐ ☐ ☐
17. After visiting the course, I feel that I have learned more about academic writing.
☐ ☐ ☐ ☐
18. I have gained more knowledge about academic writing attending the course.
☐ ☐ ☐ ☐
19. After attending the course, I want to find out more about academic writing.
☐ ☐ ☐ ☐
20. I would like to return to the course web site for information on academic writing.
☐ ☐ ☐ ☐
21. After visiting the course site, I am confident that I can write academic texts.
☐ ☐ ☐ ☐
22. In the first session you were asked to outline your expectations. Please read the copy of your submission. [Enter text from forum for participant]
Looking back, did the course meet your expectations?
☐ ☐ ☐ ☐

8 Pre-test Academic Writing

AcadWriting: Academic Writing Assessment (1) http://10.10.105.120/moodle/mod/quiz/attempt.php?q=9

LUCie - Academic Writing

You are logged in as Sabine Moebs (Logout)

LUCie ▶ AcadWriting ▶ Quizzes ▶ Academic Writing Assessment (1) ▶ Attempt 1

Update this Quiz

Info Results Preview Edit

Preview Academic Writing Assessment (1)

Start again

1
Marks: --/1

The English language is full of problems like the one presented by there, their and they're. Most native English speakers pronounce these words the same way; therefore, it is difficult for some to judge in which situation to use which spelling. Each spelling means a very different thing.

There, their or they're? Choose the right option!

Where are Mark and Sally? ______ over there. Choose...

IBM have increased ______ profits by 20%. Choose...

Submit

2
Marks: --/1

In the context of academic writing IMRD stands for:

I Intelligent
M Method for
R Research &
D Development

Answer: True
False

Submit

3
Marks: --/1

The English language is full of problems like the one presented by there, their and they're. Most native English speakers pronounce these words the same way; therefore, it is difficult for some to judge in which situation to use which spelling. Each spelling means a very different thing.

There, their or they're? Choose the right option!

I wonder if ______ going to come. Choose...

From the look on ______ faces, they're not very happy. Choose...

1 of 5 26/11/2010 11:56

Submit

4

Marks: --/1

Read the following excerpt from a journal article and indicate which section of the article it comes from.

At the Bombala site, gliders displayed a marked seasonal variation in the use of their food resources. Sap, arthropods, honeydew and manna were predominantly exploited by gliders during some months but were virtually absent from the diet during others (see Fig. 2). For example, E. viminalis sap was the main constituent in the diet during January 1984 but was not used again until April 1985. This pattern of seasonality is in agreement with that of other researchers in south-eastern Australia and appears to be largely determined by the abundance and seasonal availability of food resources. It appears, based on the limited data of food item abundance, that all items tend to vary seasonally in their availability, but although they may be quite productive, they are often patchily dispersed.

Choose one answer.

- a. Discussion
- b. Introduction
- c. Conclusion or General Discussion
- d. Results
- e. Method
- f. Abstract

Submit

5

Marks: --/1

The English language is full of problems like the one presented by there, their and they're. Most native English speakers pronounce these words the same way; therefore, it is difficult for some to judge in which situation to use which spelling. Each spelling means a very different thing.

There, their or they're? Choose the right option!

They've forgotten ______ bags.	Choose...
______ is no soap in my bathroom. Could you send some up please?	Choose...

Submit

6

Marks: --/1

Read the following excerpt from a journal article and indicate which section of the article it comes from.

The classroom research phase of the project consisted of three main teaching stages: one stage for each genre presented. The first teaching stage focussed on the model analytical expository essay 'The causes and effects of women's liberation' (see Appendix). This text was analysed in class for generic staging and cohesion. After completion of the text analysis, students and the teacher/researcher negotiated a writing checklist based on the analysis. This was followed by a 'cause and effect' group writing task. For the individual writing task which was generally completed out of class, students were asked to attach the checklists to the front of their essays and for each specified criteria on the checklist to write in their comments. Teacher/researcher comments on the student work were written in a separate column.

7

Marks: --/1

Excerpt from Woodward-Kron, R. (1994) The role of writing checklists in the teaching-learning cycle: Developing English for further study students as writers and text analyists. M.A. (TESOL) thesis. University of Technology, Sydney.

Choose one answer.

- a. introduction
- b. method
- c. results
- d. conclusion or general discussion
- e. discussion
- f. abstract

Submit

The English language is full of problems like the one presented by there, their and they're. Most native English speakers pronounce these words the same way; therefore, it is difficult for some to judge in which situation to use which spelling. Each spelling means a very different thing.

There, their or they're? Choose the right option!

From the look on ______ faces, they're not very happy.	Choose...
I know ______ considering buying a new computer system.	Choose...

Submit

8

Marks: --/1

Read the following excerpt from a journal article and indicate which section of the article it comes from.

The results for high element interactivity question scores indicated a possible difference favouring the isolated-interacting elements instruction group, F(1,16) = 3.18, MSe = 26.42, p = 0.09. The test phases main effect indicated a significant difference, F(1,16) = 31.03, MSe = 1.81, demonstrating an improvement over time. A significant interaction was displayed between the factors, F(1,16) = 11.17, MSe = 1.81. Tests of simple effects were used to explore the interaction. No difference was found between the instructional conditions at phase 1, t(16) = 0.936. At phase 2, a significant difference was indicated between the groups, t (16) = 2.43, with the isolated-interacting elements group performing at a superior level.

From: Pollock, E., Chandler, P. & Sweller, J. (in press) Assimilating complex information. Learning and Instruction.

9

Marks: --/1

Choose one answer.

- a. Introduction
- b. Method
- c. Abstract
- d. Discussion
- e. Conclusion or general discussion
- f. Results

Submit

The following sentence has been spell-checked. Although all the words are spelled correctly as far as the spell-check program is concerned, 3 usage or spelling errors remain. Type the correct sentence.

Their is considerable doubt weather this solution will be affective.

Answer:

Submit

10

Marks: --/1

In English you may reduce the restrictive relative (e.g. that) if

1. The relative clause consists only of the relative pronoun, the verb *to be*, and one or more prepositional phrases.
2. The relative clause consists of a passive verb plus some *additional*
3. The relative clause contains the relative pronouns, an adjective ending in *-ble*, and *additional* information.

Example: Pollution is a form of contamination often results from human activity.

Is the example correct?

Answer:

- True
- False

Submit

11

Marks:

The following figure shows the general structure of an academic text. Provide the labeling for the figure.
Label the figure from top to bottom and then the label replacing the question

–/1 mark. In your answer separate each term with a comma and a space; **e.g.**: image, mouse, road, distribution, question mark.

IMRDfigure

Answer:

Submit

12 Marks: –/1

The following sentence has been spell-checked. Although all the words are spelled correctly as far as the spell-check program is concerned, 2 usage or spelling errors remain. Type the correct sentence.

The initial reaction too the report has not been complementary.

Answer:

Submit

Save without submitting | Submit page | Submit all and finish

Moodle Docs for this page

You are logged in as Sabine Moebs (Logout)

AcadWriting

9 Post-test Academic Writing

Final Assessment LUCie Fall 2010 Name:

A) Please review the following text. Make sure you check for grammatical errors, punctuation and paragraph structure. Make all the corrections necessary.

Their are two key strands of program comprehension research. The first is empirical research which strives for a understanding of the cognitive processes that programmers use when understanding programs. The 2nd involves technology research with a focus on developing semi-automated tool support to improve program comprehension. This paper provides a meta-analysis of how these two strands of research are related. Empirical research in program comprehension has culminated in a wide variety of theories that provide rich explanations of how programmers understand programs and can provide advice on how program comprehension tools and methods may be improved. In response to these theories, and in some cases in parallel to theory development, many powerful tools and innovative software processes have evolved to improve comprehension activities. The field of program comprehension research has been rich and varied, with various shifts in paradigms and research cultures during the last few decades.

B) Read the following excerpt from a journal article and indicate which section of the article it comes from.

1) Section:

The Delphi study involved 25 international experts in a three-round online-study. Participants showed their level of agreement with a list of 17 hypotheses [4] and ranked them according to importance. The hypotheses concerned the impact of the use of multimedia on learning and flow experience [5] and the impact of QoS on learning and flow experience. In this paper, we consider how the experts view the impact of multimedia and QoS on learning.

2) Section:

Our research combines for the first time considerations of social connectedness, and adaptivity in adaptive e-learning systems. The proposed *connect!* module enables continuous social interaction, supporting users of adaptive e-learning systems. The initial research considers the module as outlined above.

Future works will include interfaces with some of the adaptive hypermedia systems such as AHA! and further development of adaptivity features in non-adaptive systems such as OLAT make the module suitable for those also. The benefit for systems with communication features is the option to use tools familiar to the learner and an improved accessibility of peers that are not logged into the system. The module will be tested with secondary school students of the senior cycle in a blended learning scenario over the school year 2008/2009. The test considers learning styles as a selection criteria for learner grouping and uses the *connect!* module to support stronger learner interaction and to provide feedback from the teacher. The module will be evaluated by assessing the impact on the learning results compared to students using non-adaptive system support. The *connect!* module is part of a research project that aims at delivering an adaptable system focusing on the quality of experience (QoE) of the learner. The improved communication options will make a contribution towards QoE.

C) To be as effective as possible, a paragraph should contain each of the following: unity, coherence, a topic sentence, and adequate development. Describe each term in one or two short sentences.

Unity

Coherence

Topic sentence

Adequate development

D) What part of an academic text could contain the following?
Choose from: Introduction, Background, Method, Results, Discussion, and Conclusion.

Part of Academic Text	
	Ideally, this part should be evaluative and critical of the studies which have a particular bearing on your own
	Contrary to expectations, this study did not find a significant difference between
	• indicate a problem, controversy or a gap in the field of study • define the topic or key terms
	What is now needed is a cross-national study involving
	• considering both sides of an issue, or question • considering the results of research and the implications of these.
	The design of the questionnaires was based on .
	Previous research findings into X have been inconsistent and contradictory (Smith, 1996; Jones 1999,…)
	• summarise and bring together the main areas covered in the writing, which might be called "looking back" • give a final comment or judgement on this

Appendix C - User Test Statistics

1 Course Probing

1.1 Enjoyment

1.1.1 Kruskal-Wallis Test

Test Statistics[a,b]

	Rating
Chi-Square	6.127
Df	2
Asymp. Sig.	.047
Exact Sig.	.056
Point Probability	.009

a. Kruskal Wallis Test

b. Grouping Variable: Adaptation Type

1.1.2 Median Test

Frequencies

		Adaptation Type		
		No Adaptation	QoS Adaptation	QoS MM Adaptation
Rating	> Median	4	1	8
	<= Median	16	19	12

Test Statistics[b]

	Rating
N	60
Median	3.00
Chi-Square	7.267[a]
df	2
Asymp. Sig.	.026
Exact Sig.	.030
Point Probability	.014

a. 3 cells (50.0%) have expected frequencies less than 5. The minimum expected cell frequency is 4.3.

b. Grouping Variable: Adaptation Type

1.1.3 Jonckheere-Terpstra Test

Jonckheere-Terpstra Test[a]

	Rating
Number of Levels in Adaptation Type	3
N	60
Observed J-T Statistic	745.500
Mean J-T Statistic	600.000
Std. Deviation of J-T Statistic	65.790
Std. J-T Statistic	2.212
Asymp. Sig. (2-tailed)	.027
Exact Sig. (2-tailed)	.023
Exact Sig. (1-tailed)	.011
Point Probability	.000

a. Grouping Variable: Adaptation Type

1.1.4 Mann-Whitney Test

1.1.4.1 No Adaptation – QoS Adaptation

Test Statistics[b]

	Rating
Mann-Whitney U	195.500
Wilcoxon W	405.500
Z	-.139
Asymp. Sig. (2-tailed)	.889
Exact Sig. [2*(1-tailed Sig.)]	.904[a]
Exact Sig. (2-tailed)	.833
Exact Sig. (1-tailed)	.416
Point Probability	.016

a. Not corrected for ties.

b. Grouping Variable: Adaptation Type

1.1.4.2 No Adaptation – QoS MM Adaptation

Test Statistics[b]

	Rating
Mann-Whitney U	134.000
Wilcoxon W	344.000
Z	-1.931
Asymp. Sig. (2-tailed)	.054
Exact Sig. [2*(1-tailed Sig.)]	.076[a]
Exact Sig. (2-tailed)	.075
Exact Sig. (1-tailed)	.038
Point Probability	.012

a. Not corrected for ties.

b. Grouping Variable: Adaptation Type

1.2 Experience

1.2.1 Kruskal-Wallis Test

Test Statistics[a,b]

	Rating
Chi-Square	8.186
df	2
Asymp. Sig.	.017
Exact Sig.	.015
Point Probability	.000

a. Kruskal Wallis Test

b. Grouping Variable: Adaptation Type

1.2.2 Median Test

Frequencies

		Adaptation Type		
		No Adaptation	QoS Adaptation	QoS MM Adaptation
Rating	> Median	3	2	5
	<= Median	17	18	15

Test Statistics[b]

	Rating
N	60
Median	3.00
Chi-Square	1.680[a]
df	2
Asymp. Sig.	.432
Exact Sig.	.572
Point Probability	.267

a. 3 cells (50.0%) have expected frequencies less than 5. The minimum expected cell frequency is 3.3.

Test Statistics[b]

	Rating
N	60
Median	3.00
Chi-Square	1.680[a]
df	2
Asymp. Sig.	.432
Exact Sig.	.572
Point Probability	.267

a. 3 cells (50.0%) have expected frequencies less than 5. The minimum expected cell frequency is 3.3.

b. Grouping Variable: Adaptation Type

1.2.3 Jonckheere-Terpstra Test

Jonckheere-Terpstra Test[a]

	Rating
Number of Levels in Adaptation Type	3
N	60
Observed J-T Statistic	647.500
Mean J-T Statistic	600.000
Std. Deviation of J-T Statistic	67.818
Std. J-T Statistic	.700
Asymp. Sig. (2-tailed)	.484
Exact Sig. (2-tailed)	.488
Exact Sig. (1-tailed)	.244
Point Probability	.002

a. Grouping Variable: Adaptation Type

1.2.4 Mann-Whitney Test

1.2.4.1 No Adaptation – QoS Adaptation

Test Statistics[b]

	Rating
Mann-Whitney U	128.000
Wilcoxon W	338.000
Z	-2.107
Asymp. Sig. (2-tailed)	.035
Exact Sig. [2*(1-tailed Sig.)]	.052[a]
Exact Sig. (2-tailed)	.038
Exact Sig. (1-tailed)	.019
Point Probability	.004

a. Not corrected for ties.

b. Grouping Variable: Adaptation Type

1.2.5 No Adaptation – QoS MM Adaptation

Test Statistics[b]

	Rating
Mann-Whitney U	170.500
Wilcoxon W	380.500
Z	-.909
Asymp. Sig. (2-tailed)	.363
Exact Sig. [2*(1-tailed Sig.)]	.429[a]
Exact Sig. (2-tailed)	.446
Exact Sig. (1-tailed)	.223
Point Probability	.023

a. Not corrected for ties.

b. Grouping Variable: Adaptation Type

1.3 Expectations

1.3.1 Kruskal-Wallis Test

Test Statistics[a,b]

	Rating
Chi-Square	10.487
df	2
Asymp. Sig.	.005
Exact Sig.	.004
Point Probability	.000

a. Kruskal Wallis Test

b. Grouping Variable: Adaptation Type

1.3.2 Median Test

Frequencies

		Adaptation Type		
		No Adaptation	QoS Adaptation	QoS MM Adaptation
Rating	> Median	0	4	6
	<= Median	20	16	14

Test Statistics[b]

	Rating
N	60
Median	3.00
Chi-Square	6.720[a]
df	2
Asymp. Sig.	.035
Exact Sig.	.050
Point Probability	.015

a. 3 cells (50.0%) have expected frequencies less than 5. The minimum expected cell frequency is 3.3.

Test Statistics[b]

	Rating
N	60
Median	3.00
Chi-Square	6.720[a]
df	2
Asymp. Sig.	.035
Exact Sig.	.050
Point Probability	.015

a. 3 cells (50.0%) have expected frequencies less than 5. The minimum expected cell frequency is 3.3.

b. Grouping Variable: Adaptation Type

1.3.3 Jonckheere-Terpstra Test

Jonckheere-Terpstra Test[a]

	Rating
Number of Levels in Adaptation Type	3
N	60
Observed J-T Statistic	804.000
Mean J-T Statistic	600.000
Std. Deviation of J-T Statistic	68.731
Std. J-T Statistic	2.968
Asymp. Sig. (2-tailed)	.003
Exact Sig. (2-tailed)	.003
Exact Sig. (1-tailed)	.001
Point Probability	.000

a. Grouping Variable: Adaptation Type

1.3.4 Mann-Whitney Test

1.3.4.1 No Adaptation – QoS Adaptation

Test Statistics[b]

	Rating
Mann-Whitney U	185.000
Wilcoxon W	395.000
Z	-.432
Asymp. Sig. (2-tailed)	.666
Exact Sig. [2*(1-tailed Sig.)]	.698[a]
Exact Sig. (2-tailed)	.714
Exact Sig. (1-tailed)	.357
Point Probability	.040

a. Not corrected for ties.

b. Grouping Variable: Adaptation Type

1.3.4.1.1 No Adaptation – QoS MM Adaptation

Test Statistics[b]

	Rating
Mann-Whitney U	88.000
Wilcoxon W	298.000
Z	-3.356
Asymp. Sig. (2-tailed)	.001
Exact Sig. [2*(1-tailed Sig.)]	.002[a]
Exact Sig. (2-tailed)	.001
Exact Sig. (1-tailed)	.000
Point Probability	.000

a. Not corrected for ties.

b. Grouping Variable: Adaptation Type

1.4 Time Distortion

1.4.1 Kruskal-Wallis Test

Test Statistics[a,b]

	Rating
Chi-Square	11.719
df	2
Asymp. Sig.	.003
Exact Sig.	.002
Point Probability	.000

a. Kruskal Wallis Test

b. Grouping Variable: Adaptation Type

1.4.2 Median Test

Frequencies

		Adaptation Type		
		No Adaptation	QoS Adaptation	QoS MM Adaptation
Rating	> Median	0	4	6
	<= Median	20	16	14

Test Statistics[b]

	Rating
N	60
Median	3.00
Chi-Square	6.720[a]
df	2
Asymp. Sig.	.035
Exact Sig.	.050
Point Probability	.015

a. 3 cells (50.0%) have expected frequencies less than 5. The minimum expected cell frequency is 3.3.

Test Statistics[b]

	Rating
N	60
Median	3.00
Chi-Square	6.720[a]
df	2
Asymp. Sig.	.035
Exact Sig.	.050
Point Probability	.015

a. 3 cells (50.0%) have expected frequencies less than 5. The minimum expected cell frequency is 3.3.

b. Grouping Variable: Adaptation Type

1.4.3 Jonckheere-Terpstra Test

Jonckheere-Terpstra Test[a]

	Rating
Number of Levels in Adaptation Type	3
N	60
Observed J-T Statistic	769.500
Mean J-T Statistic	600.000
Std. Deviation of J-T Statistic	68.752
Std. J-T Statistic	2.465
Asymp. Sig. (2-tailed)	.014
Exact Sig. (2-tailed)	.013
Exact Sig. (1-tailed)	.007
Point Probability	.000

a. Grouping Variable: Adaptation Type

1.4.4 Mann-Whitney Test

1.4.4.1 No Adaptation – QoS Adaptation

Test Statistics[b]

	Rating
Mann-Whitney U	168.500
Wilcoxon W	378.500
Z	-.925
Asymp. Sig. (2-tailed)	.355
Exact Sig. [2*(1-tailed Sig.)]	.398[a]
Exact Sig. (2-tailed)	.340
Exact Sig. (1-tailed)	.170
Point Probability	.000

a. Not corrected for ties.

b. Grouping Variable: Adaptation Type

1.4.4.2 No Adaptation – QoS MM Adaptation

Test Statistics[b]

	Rating
Mann-Whitney U	97.000
Wilcoxon W	307.000
Z	-3.142
Asymp. Sig. (2-tailed)	.002
Exact Sig. [2*(1-tailed Sig.)]	.005[a]
Exact Sig. (2-tailed)	.002
Exact Sig. (1-tailed)	.001
Point Probability	.001

a. Not corrected for ties.

b. Grouping Variable: Adaptation Type

1.5 Skill-Challenges Ratio

1.5.1 Kruskal-Wallis Test

Test Statistics[a,b]

	Rating
Chi-Square	.291
df	2
Asymp. Sig.	.865
Exact Sig.	.873
Point Probability	.001

a. Kruskal Wallis Test

b. Grouping Variable: Adaptation

1.5.2 Median Test

Frequencies

		Adaptation		
		No Adaptation	QoS Adaptation	QoS MM Adaptation
Rating	> Median	3	6	6
	<= Median	17	14	14

Test Statistics[b]

	Rating
N	60
Median	4.00
Chi-Square	1.600[a]
df	2
Asymp. Sig.	.449
Exact Sig.	.602
Point Probability	.199

a. 0 cells (.0%) have expected frequencies less than 5. The minimum expected cell frequency is 5.0.

Test Statistics[b]

	Rating
N	60
Median	4.00
Chi-Square	1.600[a]
df	2
Asymp. Sig.	.449
Exact Sig.	.602
Point Probability	.199

a. 0 cells (.0%) have expected frequencies less than 5. The minimum expected cell frequency is 5.0.

b. Grouping Variable: Adaptation

1.5.3 Jonckheere-Terpstra Test

Jonckheere-Terpstra Test[a]

	Rating
Number of Levels in Adaptation	3
N	60
Observed J-T Statistic	632.000
Mean J-T Statistic	600.000
Std. Deviation of J-T Statistic	67.527
Std. J-T Statistic	.474
Asymp. Sig. (2-tailed)	.636
Exact Sig. (2-tailed)	.641
Exact Sig. (1-tailed)	.321
Point Probability	.003

a. Grouping Variable: Adaptation

1.5.4 Mann-Whitney Test

1.5.4.1 No Adaptation – QoS Adaptation

Test Statistics[b]

	Rating
Mann-Whitney U	184.500
Wilcoxon W	394.500
Z	-.464
Asymp. Sig. (2-tailed)	.643
Exact Sig. [2*(1-tailed Sig.)]	.678[a]
Exact Sig. (2-tailed)	.673
Exact Sig. (1-tailed)	.336
Point Probability	.033

a. Not corrected for ties.

b. Grouping Variable: Adaptation

1.5.4.2 No Adaptation – QoS MM Adaptation

Test Statistics[b]

	Rating
Mann-Whitney U	184.000
Wilcoxon W	394.000
Z	-.479
Asymp. Sig. (2-tailed)	.632
Exact Sig. [2*(1-tailed Sig.)]	.678[a]
Exact Sig. (2-tailed)	.627
Exact Sig. (1-tailed)	.314
Point Probability	.021

a. Not corrected for ties.

b. Grouping Variable: Adaptation

1.6 QoP

1.6.1 Kruskal-Wallis Test

Test Statistics[a,b]

	Rating
Chi-Square	16.177
df	2
Asymp. Sig.	.000
Exact Sig.	.000
Point Probability	.000

a. Kruskal Wallis Test

b. Grouping Variable: Adaptation

1.6.2 Median Test

Frequencies

		Adaptation		
		No Adaptation	QoS Adaptation	QoS MM Adaptation
Rating	> Median	4	2	8
	<= Median	16	18	12

Test Statistics[b]

	Rating
N	60
Median	4.00
Chi-Square	5.217[a]
df	2
Asymp. Sig.	.074
Exact Sig.	.099
Point Probability	.040

a. 3 cells (50.0%) have expected frequencies less than 5. The minimum expected cell frequency is 4.7.

Test Statistics[b]

	Rating
N	60
Median	4.00
Chi-Square	5.217[a]
df	2
Asymp. Sig.	.074
Exact Sig.	.099
Point Probability	.040

a. 3 cells (50.0%) have expected frequencies less than 5. The minimum expected cell frequency is 4.7.

b. Grouping Variable: Adaptation

1.6.3 Jonckheere-Terpstra Test

Jonckheere-Terpstra Test[a]

	Rating
Number of Levels in Adaptation	3
N	60
Observed J-T Statistic	655.000
Mean J-T Statistic	600.000
Std. Deviation of J-T Statistic	69.987
Std. J-T Statistic	.786
Asymp. Sig. (2-tailed)	.432
Exact Sig. (2-tailed)	.437
Exact Sig. (1-tailed)	.219
Point Probability	.002

a. Grouping Variable: Adaptation

1.6.4 Mann-Whitney Test

1.6.4.1 No Adaptation – QoS Adaptation

Test Statistics[b]

	Rating
Mann-Whitney U	89.000
Wilcoxon W	299.000
Z	-3.160
Asymp. Sig. (2-tailed)	.002
Exact Sig. [2*(1-tailed Sig.)]	.002[a]
Exact Sig. (2-tailed)	.002
Exact Sig. (1-tailed)	.001
Point Probability	.000

a. Not corrected for ties.

b. Grouping Variable: Adaptation

1.6.4.2 No Adaptation – QoS MM Adaptation

Test Statistics[b]

	Rating
Mann-Whitney U	160.500
Wilcoxon W	370.500
Z	-1.175
Asymp. Sig. (2-tailed)	.240
Exact Sig. [2*(1-tailed Sig.)]	.289[a]
Exact Sig. (2-tailed)	.283
Exact Sig. (1-tailed)	.141
Point Probability	.043

a. Not corrected for ties.

b. Grouping Variable: Adaptation

2 Regression Analysis Post Survey

2.1 QoP- Experience

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.276[a]	.076	.005	.50050

a. Predictors: (Constant), QoP

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.269	1	.269	1.072	.319[a]
	Residual	3.256	13	.250		
	Total	3.525	14			

a. Predictors: (Constant), QoP

b. Dependent Variable: Experience

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.609	.445		3.618	.003
	QoP	.248	.239	.276	1.035	.319

a. Dependent Variable: Experience

2.2 QoP – Flow

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.338[a]	.114	.046	.520

a. Predictors: (Constant), QoP

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.453	1	.453	1.675	.218[a]
	Residual	3.517	13	.271		
	Total	3.970	14			

a. Predictors: (Constant), QoP

b. Dependent Variable: Flow

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.383	.462		2.992	.010
	QoP	.322	.249	.338	1.294	.218

a. Dependent Variable: Flow

2.3 QoP – Learning

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.167[a]	.028	-.047	.434

a. Predictors: (Constant), QoP

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.071	1	.071	.375	.551[a]
	Residual	2.447	13	.188		
	Total	2.517	14			

a. Predictors: (Constant), QoP

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.071	1	.071	.375	.551[a]
	Residual	2.447	13	.188		
	Total	2.517	14			

a. Predictors: (Constant), QoP

b. Dependent Variable: Learning

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.961	.386		5.085	.000
	QoP	.127	.208	.167	.613	.551

a. Dependent Variable: Learning

2.4 Flow - Learning

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.398[a]	.158	.094	.40372121

a. Predictors: (Constant), Flow

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.398	1	.398	2.445	.142[a]
	Residual	2.119	13	.163		
	Total	2.517	14			

a. Predictors: (Constant), Flow

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.398	1	.398	2.445	.142[a]
	Residual	2.119	13	.163		
	Total	2.517	14			

a. Predictors: (Constant), Flow

b. Dependent Variable: Learning

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.567	.410		3.825	.002
	Flow	.317	.203	.398	1.564	.142

a. Dependent Variable: Learning

2.5 Learning - Flow

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.398[a]	.158	.094	.5070219

a. Predictors: (Constant), Learning

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.628	1	.628	2.445	.142[a]
	Residual	3.342	13	.257		
	Total	3.970	14			

a. Predictors: (Constant), Learning

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.628	1	.628	2.445	.142[a]
	Residual	3.342	13	.257		
	Total	3.970	14			

a. Predictors: (Constant), Learning

b. Dependent Variable: Flow

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.863	.711		1.214	.246
	Learning	.500	.320	.398	1.564	.142

a. Dependent Variable: Flow

2.6 Flow – Experience

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.521[a]	.272	.216	.44439

a. Predictors: (Constant), Flow

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.958	1	.958	4.850	.046[a]
	Residual	2.567	13	.197		
	Total	3.525	14			

a. Predictors: (Constant), Flow

b. Dependent Variable: Experience

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	1.090	.451		2.416	.031
	Flow	.491	.223	.521	2.202	.046

a. Dependent Variable: Experience

2.7 Learning - Experience

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.675[a]	.455	.413	.38432

a. Predictors: (Constant), Learning

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.605	1	1.605	10.866	.006[a]
	Residual	1.920	13	.148		
	Total	3.525	14			

a. Predictors: (Constant), Learning

b. Dependent Variable: Experience

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.304	.539		.564	.582
	Learning	.798	.242	.675	3.296	.006

a. Dependent Variable: Experience

2.8 QoP – Experience

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.256[a]	.065	-.001	.491

a. Predictors: (Constant), QoP

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.236	1	.236	.979	.339[a]
	Residual	3.373	14	.241		
	Total	3.609	15			

a. Predictors: (Constant), QoP

b. Dependent Variable: Experience

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.617	.436		3.708	.002
	QoP	.231	.234	.256	.990	.339

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	1.617	.436		3.708	.002
	QoP	.231	.234	.256	.990	.339

a. Dependent Variable: Experience

2.9 Usability – Experience

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.698[a]	.488	.448	.373

a. Predictors: (Constant), Usability

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.719	1	1.719	12.375	.004[a]
	Residual	1.806	13	.139		
	Total	3.525	14			

a. Predictors: (Constant), Usability

b. Dependent Variable: Experience

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.919	.336		2.737	.017
	Usability	.447	.127	.698	3.518	.004

a. Dependent Variable: Experience

Glossary

Adaptive hypermedia	Adaptive hypermedia systems “tailor content presentation and navigation support to individual users by taking into account a model of user’s goals, interests, and preferences” [25]
Bandwidth	Systems are connected by communication links. Different links can transmit data at different rates. The link transmission rate is [..] called the bandwidth of the link, which is typically measured in bits/second. [133]
Delay	The delay of an IP packet within an IP network. As a packet travels from one node to the subsequent node along this path, the packet suffers from delays at each node. The most important of these are the nodal processing delay, queuing delay, transmission delay and propagation delay; together, these delays accumulate to give a total nodal delay. [133]
Flow experience	The concept of flow was first introduced by Csikszentmihalyi [41] and it represents the optimal experience or complete absorption with an activity. It is characterized by 8 dimensions, which can be divided into three stages: antecedents, experiences and effects. The dimensions allocated to the antecedent stage are a clear set of goals, immediate feedback and equilibrium between challenges and skills. The experience stage is characterized by the merging of action and awareness, focused concentration and a sense of potential control. The final effects stage is characterized by a loss of self-consciousness, time distortion and a self-rewarding experience.
Jitter	For applications such as audio and video streaming, it does not matter much if the packets take 20 msec or 30 msec to be delivered, as long as the transit time is constant. The variation in the packet arrival times is called jitter. [209]

Packet Loss	Because queue capacity is finite, packet delays do not approach infinity; instead a packet can arrive to find a full queue. With no place to store such a packet a router will drop the packet; the packet will be lost. [133]
Multimedia applications	Streaming video, IP telephony, Internet radio, teleconferencing, interactive games, virtual worlds. Three broad classes of multimedia applications are streaming stored audio/video, streaming live audio/video and real-time interactive audio and video. [133] Multimedia presentations integrate streaming audio and video with images, text or any other media type. [17]
Quality of Perception	Quality of Perception characterizes the perceptual experience of the user when interacting with multimedia applications. [79]
Quality of Experience	The overall acceptability of an application or service, as perceived subjectively by the end-user. [117]
Quality of Service	The collective effect of service performance, which determine the degree of satisfaction of a user of the service. [59]
Usability	Usability is a quality attribute that assesses how easy user interfaces are to use. The word "usability" also refers to methods for improving ease-of-use during the design process. Usability is defined by 5 quality components: learnability, efficiency, memorability, error handling and satisfaction. [164]
User Experience	User Experience is about technology that fulfils more than just instrumental needs in a way that acknowledges its use as a subjective, situated, complex and dynamic encounter. It is a consequence of a user's internal state, the characteristics of the designed system and the context within which the interaction occurs. [96]