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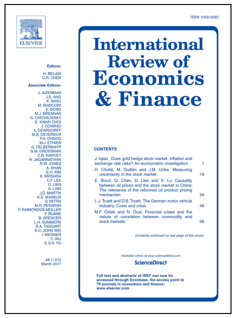

Financial perceptions and AI infringement risks

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ABSTRACT

Artificial intelligence (AI)-related intellectual property (IP) infringement involves the unauthorized use of copyrighted materials during model training and the creation of content that may violate copyright, trademark, or patent laws. This phenomenon presents critical financial risks for businesses, ranging from reputational harm and erosion of brand equity to potential litigation, regulatory scrutiny, and increased investor uncertainty. This study explores how to understand this emergent risk and the associated implications. To do so, we apply social capital theory to an analysis of 10,447 Chinese social media users' reactions to China's first AI-generated voice infringement lawsuit. Our findings suggest that out-tie social capital (exposure to diverse networks) tends to promote neutral or positive views, while in-tie social capital (strong, close-knit communities) initially encourages favourable attitudes but shifts toward ethical and risk concerns when potential financial damages are perceived. Our study, thus, highlights the interplay between social perception and corporate financial considerations in an era where AI increasingly shapes economic opportunities and liabilities.

Keywords: AI infringement, financial perceptions, social capital, large language models, corporate value maximisation

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Artificial intelligence (AI)-related intellectual property (IP) infringement involves the unauthorized use of copyrighted materials during model training and the creation of content that may violate copyright, trademark, or patent laws. This phenomenon presents critical financial risks for businesses, ranging from reputational harm and erosion of brand equity to potential litigation, regulatory scrutiny, and increased investor uncertainty. This study explores how to understand this emergent risk and the associated implications. To do so, we apply social capital theory to an analysis of 10,447 Chinese social media users' reactions to China's first AI-generated voice infringement lawsuit. Our findings suggest that out-tie social capital (exposure to diverse networks) tends to promote neutral or positive views, while in-tie social capital (strong, close-knit communities) initially encourages favourable attitudes but shifts toward ethical and risk concerns when potential financial damages are perceived. Our study, thus, highlights the interplay between social perception and corporate financial considerations in an era where AI increasingly shapes economic opportunities and liabilities.

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1. INTRODUCTION

Artificial intelligence (AI) has rapidly become a key driver of corporate strategy and market valuation, offering firms new ways to extract, analyse, and monetize data. From a financial perspective, AI's potential to enhance operational efficiency, personalize consumer experiences, and deepen customer engagement can elevate intangible assets like brand equity and goodwill (Durante et al., 2024). Because these intangible assets increasingly underpin firm valuation, companies that leverage AI effectively can attract stronger investment and maintain competitive advantages. Yet, AI simultaneously introduces new forms of financial risk, such as inadvertent or deliberate infringement of intellectual property rights (IPRs), which can expose firms to lawsuits, regulatory fines, and reputational harm. In this study, we argue that the trade-off between financial value and financial risk is particularly shaped by consumers' perceptions of product value, which are, in turn, influenced by their form of social capital.

AI's role in boosting social capital is also connected to economic outcomes. Generative AI tools like ChatGPT and its myriad competitors (Epstein et al., 2023) enable rapid content creation that can deepen engagement within existing user communities (a form of in-tie social capital). While platforms powered by technology such as Neomotro[1] and Liquid Neural Networks (LNNs) (Rathi et al., 2023) facilitate real-time content personalization and broaden online ties (a form of out-tie social capital). These benefits may bolster brand loyalty and reduce marketing costs, thereby influencing firm value. However, the very processes that enable this innovation - such as training on large datasets - can complicate the protection of existing IP frameworks if original content is used or reproduced without consent.

[1] To learn more about Neomotron: https://developer.nvidia.com/blog/leverage-our-latest-open-models-for-synthetic-data-generation-with-nvidia-nemotron-4-340b/

The convergence of AI-driven content creation and expanding digital marketplaces has intensified concerns over infringement, especially involving copyrighted materials and trademarks (Appel, Neelbauer, and Schweidel, 2023; Samuelson, 2024). Large training datasets may contain proprietary text, images, or other assets, creating exposure to legal liability if proper permissions are not obtained. Beyond direct legal costs, there is a financial ripple effect: diminished brand equity, negative investor reactions, and increased scrutiny regarding corporate governance and ethics (Samuelson, 2023).

Several high-profile lawsuits underscore the potential legal, financial, and reputational consequences firms may face. For instance, Stability AI, Midjourney, and DeviantArt were sued by a group of artists in 2023 for allegedly using copyrighted artwork without consent to train AI models[2]. In a related case, Getty Images initiated legal action in both the UK and the US against Stability AI, accusing it of using millions of copyrighted images without authorization to develop its generative tools[3]. Similarly, OpenAI and Microsoft faced a class-action lawsuit in 2022 over GitHub Copilot, which developers allege was trained on public code repositories in violation of open-source licenses[4].

In response to these challenges, regulatory frameworks are beginning to evolve. The European Union's AI Act (EU AI Act) and the AI Liability Directive (AILD)[5] aim to clarify accountability for AI-generated outputs, including under copyright law. Meanwhile, U.S. courts have become a testing ground for the boundaries of fair

[2] To learn more about this lawsuit: https://www.reuters.com/legal/litigation/artists-take-new-shot-stability-midjourney-updated-copyright-lawsuit-2023-11-30/
[3] To learn more about this lawsuit: https://www.herbertsmithfreehills.com/notes/ip/2025-01/navigating-representative-actions-takeaways-from-getty-images-v-stability-ai
[4] To learn more about this lawsuit: https://www.legal.io/articles/5516216/Judge-Throws-Out-Majority-of-Claims-in-GitHub-Copilot-Lawsuit
[5] To learn more about the EU AI Act and AILD: https://www.skadden.com/insights/publications/2023/12/2024-insights/other-regulatory-developments/ai-in-2024

use and licensing obligations in the AI context[6]. In China, the subject nation of this study, courts are increasingly enforcing IP protections against AI-generated content, including digital art and synthetic voices, signaling a heightened regulatory posture[7]. These legal developments underscore the urgent need for firms to adopt robust IP compliance and risk mitigation strategies. Without these safeguards, companies face increased exposure to litigation, regulatory penalties, diminished investor confidence, and potential long-term value erosion in their AI-related ventures.

Although firms and regulators are becoming more vigilant about AI-related IP infringement, the role of consumer perception remains underexamined. This is an important oversight, as consumer perception can profoundly affect brand reputation, user engagement, revenue growth, and – ultimately - financial valuation (Puntoni, Reczek, Giesler, and Botti, 2021). When consumers are indifferent to the legal and ethical dimensions of AI-driven content, companies may deprioritize strict compliance measures and focus on rapid innovation. Alternatively, if consumers express ethical objections or fear financial harm to creators, public trust can deteriorate swiftly, sparking reputational damage and pressure from shareholders concerned about long-term value erosion.

Drawing on social capital theory, this study posits that consumers' network structures influence how they perceive the financial and ethical implications of AI use. Out-tie social capital exposes individuals to a range of perspectives, which can normalize AI-driven creativity and reduce the perceived severity of potential IP conflicts. In-tie social capital, built on tighter, trust-based bonds, may initially foster enthusiasm for AI-enabled communities but can turn critical once the discussion

[6] To learn more about these lawsuits in the U.S.: https://www.bakerlaw.com/services/artificial-intelligence-ai/case-tracker-artificial-intelligence-copyrights-and-class-actions/
[7] To learn more about this infringement case in China: https://techinsights.linklaters.com/post/102j4cb/china-first-ai-output-copyright-infringement-case

shifts to tangible economic harm (Makarius, Mukherjee, Fox, and Fox, 2020). Moreover, explicit financial framing -highlighting costs to creators, litigation expenses, or broader market impacts - can amplify public scepticism toward AI ethics and content legitimacy.

To make our theory more explicit (albeit at the slight risk of over-simplifying), we are effectively saying that utilising Generative AI tools, such as ChatGPT, to build in-tie social capital such as creating closer relationships, is subject to risks if users understand that these closer relationships are built on the intellectual property of others. While this risk is not present for use of AI tools that instead enable users to better interact with a broader community (that is, to build out-tie social capital).

To investigate how social capital intersects with perception of financial risk in AI-related infringement, we analyze user reactions on a large Chinese social media platform following the country's first AI-generated voice infringement lawsuit. We first quantify the impact of in-tie and out-tie social capital on consumer attitudes toward AI-related IP infringement. Next, we examine the moderating role of financial framing to understand whether highlighting economic losses or legal penalties shifts sentiment. That then allows us to highlight the implications around firm value, corporate governance, and investment risk.

We employ a fine-tuned large language model (LLM) - Bidirectional Encoder Representations from Transformers (BERT) (Huang, Wang, and Yang, 2023) alongside the FastTextRank algorithm (Liu et al., 2024) to manage the complexity of over ten thousand user comments. These text analytics methods allow for detailed sentiment and thematic analysis. By incorporating social capital theory into our interpretation of these results, we bridge AI-focused legal scholarship with the financial literature on corporate valuations, intangible asset management, and risk mitigation.

Our findings indicate that out-tie social capital fosters generally favorable or tolerant views of AI-driven innovation. In-tie social capital likewise supports positive perceptions initially but shifts toward concern over ethical and financial risks once the conversation highlights potential harm to creators' revenues or to a firm's brand value. Notably, when IP infringement is framed as a financial problem - emphasizing litigation costs or investor uncertainty - overall trust in AI diminishes, revealing consumers' heightened skepticism about ethical standards.

By showing that consumer perceptions are fluid and subject to financial cues, this study highlights the necessity for firms and regulators to develop multifaceted strategies that address both the social and economic dimensions of AI deployment. For finance scholars and practitioners, the Chinese context offers broader insights into how culturally shaped social networks can affect intangible asset protection and shareholder confidence. Proactively aligning AI-driven innovation with ethical and legal safeguards may help firms maintain strong investor support, preserve brand equity, and avoid costly disputes. There may also be more certainty over the value created from firms investing in building out-tie social capital for their users, if there is likely to be a general societal difficulty in persuading users of tools for in-tie social capital that the product has a net benefit.

2. LITERATURE REVIEW AND HYPOTHESES

2.1. The Economic Perspective on AI-Related Infringement

AI-related infringement encompasses a range of legal violations that arise from the ways AI technologies are developed, trained, and deployed (Teli, Rai, and Lin, 2024). As AI advances, particularly through machine learning and generative models, it increasingly engages with vast datasets that can contain sensitive, proprietary, or legally protected information (Jo, 2023). From a financial perspective, such proprietary or legally protected content often contributes significantly to a firm's intangible asset portfolio—comprising brand equity, patents, or copyrighted works that can underpin future revenue streams and, thus, affect overall market valuation. When AI systems process, replicate, or transform these elements without permission, they not only risk legal penalties but also diminish the financial value that intellectual property (IP) protections are designed to preserve.

For instance, if an AI model is trained on personal data obtained without appropriate licensing, it may undermine the contractual or economic arrangements that protect data as a monetizable corporate resource, exposing developers or user platforms to potential lawsuits and reputational harm (Jo, 2023) as well as violate privacy laws, such as General Data Protection Regulation (GDPR: Evans, Hajli, and Nisar, 2023). Similarly, AI-generated representations of individuals can infringe upon publicity rights, leading to damage claims that adversely affect a firm's cash flows and deter existing or potential investors. These developments underscore that AI's expansive capabilities can introduce not only legal ambiguities but also material financial risks, especially in industries where intangible assets heavily influence share price and cost of capital.

Unlike previous technological advancements (Cappelli, Corsino, Laursen, and Torrisi, 2023; Huang, Li, Shen, and Wang, 2024), AI-related infringement involves autonomous or semi-autonomous systems whose creative outputs blur traditional boundaries of authorship and ownership (Samuelson, 2023). This blurring heightens the possibility of inadvertently replicating trademarked or copyrighted elements in AI-generated content, raising both immediate litigation costs and longer-term threats to firm reputation—two factors that can be critical to investor sentiment and valuations. Companies relying on AI-based content generation face unprecedented challenges in monitoring and governing these outputs, potentially weakening their IP portfolios' perceived strength, which is often central to a firm's financial health (Samuelson, 2024). The extent to which AI autonomously synthesizes training data can leave corporate managers and legal departments in uncertain territory about infringement liability, hampering strategic financial planning in IP-centric industries.

Among these forms of infringement, IP infringement is particularly prominent due to the nature of generative AI, which can produce text, images, audio, and video that closely resemble copyrighted works (Appel, Neelbauer, and Schweidel, 2023; Samuelson, 2024, Wang et al., 2024). This close resemblance jeopardizes the exclusivity that IP rights are meant to protect - exclusivity that, in many cases, forms the basis of competitive advantage and long-term firm valuation (Castaldi, Giuliani, Kyle, and Nuvolari, 2024). In a market environment where intangible assets often dwarf tangible assets on corporate balance sheets, unauthorized use of copyrighted elements not only introduces immediate legal threats but can also erode the core value proposition that IP-intensive firms provide to investors. As AI's transformative capabilities become more widespread, developing robust strategies for managing IP infringement risks becomes crucial - not merely from a legal standpoint but also to sustain investor confidence and protect financial performance in the AI-driven era.

2.2. AI-Related IP Infringement and Social Capital

Rooted in social capital theory (Hock-Doepgen, Heaton, Clauss, and Block, 2024; Shi, Wang, Kang, and Sun, 2023; Sun, Cappa, Zhu, and Peruffo, 2023), this research examines AI-related IP infringement in the context of consumers' social network development - a critical concept in the digital economy era. Social capital refers to the social and economic value derived from an individual's connections on social media and other networking platforms (Brennecke, Ertug, and Elfring, 2024). This capital can be segmented into two main types: out-tie capital and in-tie capital. Out-tie capital represents the networks or accounts that individuals choose to follow or subscribe to, allowing them to access diverse information, viewpoints, and resources. In-tie capital, conversely, reflects followers or subscribers a user has: an indicator of that individual's reach, influence, and authority within a social-ecological system (Jahel et al., 2023).

AI's capability to assist in content creation, personalization, and audience analysis holds the potential to substantially enhance both in-tie and out-tie capital for consumers and creators (Wang et al., 2024). For instance, AI-generated content can broaden brand or user appeal by producing engaging media, while AI-driven recommendations connect individuals with relevant influencers or communities. In financial terms, strong social capital can bolster intangible assets such as brand equity, contributing to a more favourable risk profile for content platforms. Yet the same processes that drive these benefits - like relying on large datasets or generating synthetic media - can undermine IP protections. If users or platforms repeatedly violate IP rights via AI-generated content, they not only jeopardize user trust but also introduce legal uncertainties that can reduce the platform's enterprise value or lead to investor scepticism (Samuelson, 2023). Hence, understanding IP infringement dynamics within social capital is essential for firms seeking to balance user engagement against potential financial liabilities.

2.2.1. Benefits of AI Technology

The growth of AI technology brings various advantages for consumers, such as content creators (Jung, Nam, Choi, and Park, 2025; Saffarizadeh, Keil, and Maruping, 2024), who aim to expand their social capital, as summarized in Table 1. By leveraging AI, consumers can produce engaging, diverse, and high-quality media that attracts more followers, thus boosting their in-tie capital. This increased reach can translate into stronger personal branding or monetization channels, each of which can have meaningful economic implications. AI-generated content, often visually compelling, dynamic, and even interactive, helps creators maintain audience interest, fostering brand loyalty - an intangible asset that can be highly valuable for individual influencers and firms alike.

-------- Insert Table 1 about here --------

AI's role also extends to cross-platform sharing and visibility (Hajli, Saeed, Tajvidi, and Shirazi, 2022), contributing to the expansion of out-tie capital. More extensive digital footprints create potential for stronger market presence and, in the case of businesses, can lead to higher valuation multiples tied to user growth and content virality. Further, AI-powered personalization and recommendation systems (Kumar, Ashraf, and Nadeem, 2024) help tailor content to specific user preferences, thereby enhancing engagement metrics and follower retention - key indicators that often matter to advertisers, investors, and financial analysts assessing the viability of digital platforms.

Finally, AI-driven analytics provide creators with performance insights (Hajli et al., 2022; Kumar et al., 2024). These analytics inform strategic decisions on content production and audience targeting, allowing creators to optimize their outputs for maximum engagement or revenue generation. In a financial sense, such data-driven optimizations can reduce marketing costs, improve return on investment, and mitigate risks by detecting potential copyright overlaps early, before litigation or regulatory penalties occur. Collectively, these AI-powered benefits illustrate the possibility of building robust social networks to enhance brand equity, goodwill, and, ultimately, firm value.

2.2.2. Infringement Risks in AI

Despite these benefits, the use of AI in social capital development also introduces potential risks, particularly related to IP infringement (as summarised in Table 1). AI-generated content may unintentionally include copyrighted materials if the training datasets contain protected elements (Samuelson, 2023), leading to legal challenges and reputational harm. Such events carry direct costs (litigation, fines, or settlements) and can also erode the intangible assets that underlie firm valuation. Personalization and recommendation algorithms (Kumar et al., 2024), which rely heavily on user data, raise additional concerns. Failure to manage data properly can result in compliance risks, which often trigger shareholder or regulatory scrutiny affecting a firm's financial stability. Moreover, synthetic media like AI-generated personas (Marion, Srour, and Piller, 2024) adds the possibility of likeness misuse, with ensuing claims that not only bring about legal costs but may also spark negative investor reactions if perceived as unethical or exploitative.

Potential IP infringement risks carry significant consequences across various dimensions, as outlined in Table 2. From a financial viewpoint, AI-driven IP violations can disrupt market dynamics by allowing infringers to leverage unlicensed works at lower production costs, undermining fair competition (Samuelson, 2023). This undercuts original creators' revenue streams and can distort valuations in creative and data-driven sectors (Krakowski, Luger, and Raisch, 2023). Investors, wary of legal hazards associated with unauthorized data use, may reduce funding or divest from companies seen as operating in legally grey areas, which can influence cost of capital and hamper investment in innovation. At the same time, reputational damage stemming from IP controversies can degrade corporate brand equity, a key intangible asset that often correlates with favourable valuation multiples.

-------- Insert Table 2 about here --------

Legal and ethical ramifications further exacerbate financial risks. As Du and Xie (2021) note, an evolving legal environment around AI can introduce compliance uncertainties that disrupt corporate strategies. Each jurisdiction may enforce different standards, making global firms particularly susceptible to cross-border litigation expenses. Ethically, unauthorized IP and data exploitation can erode consumer and shareholder trust. A loss of confidence from stakeholders can manifest in stock price volatility, rating downgrades, or higher financing costs. Additionally, in ecosystems where IP is a primary driver of competitive advantage, infringement concerns may stifle open innovation (Grimaldi, Greco, and Cricelli, 2021) and deter data-sharing partnerships (Kazantsev et al., 2023). Firms that cannot ensure robust compliance and risk management strategies can see these intangible risks materialize in their market value over time.

In response, several proactive measures can help firms and creators reap AI's benefits while navigating potential legal and ethical challenges (Table 1). Establishing standardized licensing frameworks for AI training datasets (Murtarelli, Gregory, and Romenti, 2021; Yan et al., 2024) is one option: properly licensed inputs reduce the probability of infringement claims that might upset investor confidence. Digital watermarking technologies (Chen et al., 2024) can protect proprietary content by embedding traceable markers, making it easier to track any unauthorized usage and thereby mitigating reputational and legal fallout. When it comes to AI-driven personalization or recommendation systems (Kumar et al., 2024), rigorous data-use policies and anonymization protocols (Ni, Cang, Gope, and Min, 2022) can bolster investor trust that user data is being handled responsibly. Similarly, strict guidelines for managing synthetic personas (Ahmad, 2024) can pre-empt potential lawsuits regarding misappropriation of likeness, further safeguarding firms from unanticipated liabilities. By integrating these solutions into their AI adoption strategies, stakeholders can potentially minimize legal uncertainties and fortify the intangible assets that sustain long-term financial performance.

2.3. Consumer Attitudes Toward AI-Related IP Infringement

Understanding consumer attitudes toward AI-related IP infringement is critical for several reasons, especially as AI-generated content becomes increasingly prevalent (Giroux, Kim, Lee, and Park, 2022; Vlačić, Corbo, e Silva, and Dabić, 2021). Consumers' views on whether AI improperly displaces original creativity affect not only their immediate willingness to engage with a product but also longer-term brand loyalty and brand equity - factors that can influence a firm's valuation and access to capital (Puntoni, Reczek, Giesler, and Botti, 2021). If consumers perceive AI-related IP infringement as unethical or unfair, negative sentiment can spread quickly, damaging brand perception and ultimately weakening revenue streams or share price. Conversely, more lenient consumer attitudes may signal to companies that they can employ AI-driven innovation with relatively low reputational risk, creating strategic opportunities for cost savings, product differentiation, or new revenue sources.

Moreover, consumer attitudes often shape the broader policy and legal environment, which in turn influences how firms plan and budget for potential infringement. Politically salient public concerns can sway lawmakers toward stricter regulations, raising legal compliance costs and possibly deterring AI investments (Doloreux and Turkina, 2021). On the other hand, if the public shows acceptance or indifference, policymakers may be less compelled to impose tight legal frameworks, allowing businesses to allocate capital more aggressively toward AI-related growth. Thus, consumers' perceptions of AI-related IP infringement have material consequences for corporate risk assessment, capital allocation decisions, and ongoing compliance strategies.

2.3.1. Direct impacts of social capital

As shown in Figure 1, we propose that consumers' social capital - the breadth and depth of their connections on social media - can benefit from AI advancements, which, in turn, significantly shape their attitudes toward AI-related IP infringement.

Individuals embedded in expansive networks encounter a diversity of AI-created works and debates, enriching their knowledge of both the creative possibilities and financial stakes of AI. Social capital also fosters shared norms within these communities, including attitudes on which uses of AI are considered beneficial for overall economic progress versus those seen as detrimental to creators' or investors' interests.

-------- Insert Figure 1 about here --------

We first propose that out-tie social capital — represented by the extent to which individuals follow others — exposes consumers to a diversity of perspectives and novel information. Individuals with high out-tie social capital are more likely to be exposed to heterogeneous content, including the latest technological innovations and discourse surrounding them (Brennecke et al., 2024). In digital spaces, these individuals engage with a broad array of creators, thought leaders, and influencers, which likely enhances their awareness of both the potentials and limitations of AI-generated content. Repeated exposure to AI tools and applications can gradually normalize these technologies, leading to more accepting attitudes toward their by-products — even when those by-products exist in legally or ethically grey areas. The normalization effect may lead consumers to emphasize the macro-level advantages of AI, such as economic stimulation, improved firm valuation, and creative acceleration, while minimizing concerns about ownership and originality.

In this sense, high out-tie consumers may not perceive AI-related IP infringement as inherently problematic. Instead, they may frame such occurrences as growing pains of innovation or as necessary trade-offs for broader technological and economic advancement. Social capital can influence norms and collective judgments, as frequent exposure to certain behaviors or beliefs — particularly within diverse networks — can legitimize those beliefs. Thus, consumers with high out-tie social capital may develop neutral or even favorable attitudes toward AI-related IP infringement, especially if it aligns with their broader perception of AI as a force for progress. Hence:

H1. *Consumers with higher out-tie social capital are more likely to exhibit neutral or positive attitudes toward AI-related IP infringement.*

In parallel, we consider the role of in-tie social capital—those connections directed toward an individual, as represented by the number of followers they have. Consumers with high in-tie social capital typically occupy influential positions within their digital ecosystems. Their high visibility and content output mean that they are not only consumers but also producers of digital content. For such individuals, AI technologies can be practical tools that enhance productivity, reduce content creation time, and ensure consistency in messaging. AI tools offer significant operational efficiencies, which can be particularly attractive to users who must regularly engage their audience to maintain influence and visibility (Saffarizadeh et al., 2024).

From this vantage point, AI is a means of sustaining online relevance and even generating revenue. The pragmatic adoption of AI tools by high in-tie users may result in a utilitarian view of IP concerns, where the advantages of increased efficiency, platform growth, and monetization outweigh the abstract or long-term risks of IP infringement. Such users may also perceive themselves as immune to the legal and reputational risks associated with infringement, particularly if they assume that responsibility lies with the platform or the tool developers.

Moreover, individuals with substantial in-tie social capital often shape the attitudes of their followers, further reinforcing their own perspectives. As a result, they may become active proponents of AI utility and downplay associated risks to maintain a coherent and persuasive personal brand. This dynamic reinforces a positive or neutral attitude toward AI-related IP infringement. Thus:

H2. *Consumers with higher in-tie social capital tend to display neutral or positive attitudes toward AI-related IP infringement.*

2.3.2. Moderating impacts of financial perceptions of AI

Consumers' financial perceptions of AI, whether seen as a source of cost savings and profit expansion (e.g., Saffarizadeh et al., 2024) or as a driver of litigation and royalty payments (Samuelson, 2024), can add a decisive layer to how social capital affects attitudes toward AI-related IP. Where consumers see AI-driven content creation as a boon to service delivery, any infringement issues may be downplayed or dismissed. Conversely, if they perceive AI to threaten established and accepted economic models or to impose unmanageable liabilities, their tolerance for AI-related infringement is likely to decrease. In short, when financial stakes become salient, consumers' acceptance of AI often becomes contingent on whether the associated risks appear containable or are outweighed by expected returns.

We contend that consumers with high out-tie social capital may become more skeptical of AI's implications if they begin to perceive it as financially harmful. Despite their exposure to a diversity of opinions, a consistent narrative about AI-induced income losses for creators or escalating legal liabilities could trigger a reassessment of their previously neutral or positive views. This shift occurs because the cost-benefit analysis becomes more salient: if AI is seen not just as innovative but as a threat to the financial wellbeing of the creative economy (Samuelson, 2024), consumers may recalibrate their stance.

Importantly, even in diverse networks, dominant themes or concerns—especially financially framed ones—can exert strong influence on norm formation. Thus, financial perceptions act as a reality check, anchoring otherwise optimistic consumers in more pragmatic evaluations of AI’s long-term viability and ethical soundness:

H3. *Consumers’ financial perception of AI reduces the strength of the relationship between their out-tie social capital and attitudes toward AI-related IP infringement.*

Similarly, we argue that among consumers with high in-tie social capital, a heightened awareness of the financial impact of AI can create ambivalence. Consumers with many followers benefit from AI’s ability to scale up content production efficiently and cost-effectively (Saffarizadeh et al., 2024). However, once financial concerns become salient — such as legal exposure, royalty costs, or reputational risks — these benefits may be re-evaluated. Legal liabilities associated with AI-generated content are growing, and these risks directly impact content creators, especially those with large followings (Samuelson, 2023).

Moreover, AI-generated content may threaten the originality that high in-tie users rely on to maintain brand identity and follower loyalty. If audiences detect overuse of AI or question the authenticity of content, it can reduce engagement, influence, and associated revenue (Samuelson, 2024). These users may also face reputational backlash if perceived as prioritizing convenience over ethical or legal standards.

As such, financial concerns weaken the initially positive effect of in-tie social capital on support for AI-related IP infringement. Heightened awareness of economic risks leads influential users to reassess the long-term sustainability and legal viability of their AI usage:

H4. *Consumers' financial perception of AI weakens the effect of their in-tie social capital on attitudes toward AI-related IP infringement.*

A broader perspective on the financial aspect, that cannot be directly tested in the study but is an implication, is that there is a clear relationship between customer perceptions and investment valuation. Financial analysts use consumer sentiment when valuing the growth opportunities of firms (Luo, Homburg, and Wieseke, 2010) and, thus, we would expect this consumer perceptions to feed through to valuation metrics.

2.4. In the Chinese Context

This study uses a case of AI-related IP infringement in China to explore how consumers' social capital influences attitudes toward emerging technological risks in a rapidly evolving market. In Chinese society, social capital, both in personal networks and in digital platforms, significantly shapes collective views on new technology (Xiao and Anderson, 2022). Moreover, China's vibrant tech sector is home to some of the world's largest AI-driven platforms (Liu, Chang, Forrest, and Yang, 2020; Tao, Weng, Chen, ALHussan, and Song, 2024). This environment intensifies financial considerations related to IP: firms seek competitive advantage in a huge domestic market but must manage complex regulatory frameworks and rising user expectations for ethical content creation (Hong, Edler, and Massini, 2022).

Studying consumer attitudes within this context highlights the crucial role of social networks in determining how new technological risks, such as IP infringement, impact intangible asset protection and overall market confidence. On one hand, strong network ties reinforce norms around rapid adoption, fuelling AI-driven growth that can be attractive to investors. On the other, Chinese courts' increasing willingness to penalize AI-enabled IP infringements suggests potential financial vulnerabilities for firms that cannot demonstrate robust compliance or brand protection. Consequently, China's experience underscores that responsible AI governance and comprehensive risk mitigation strategies go beyond legal considerations: they are vital for securing brand credibility, investor trust, and long-term valuation in a digital marketplace where social capital and financial markets intersect.

3. METHODS

3.1. Data Collection

Our study leverages data from Weibo, one of China's most popular social media platforms, with 584 million monthly active users (Statista, April 2024), to explore how consumers' social capital affects their perceptions of AI-related IP infringement. Weibo's significance lies in its broad and active user base, representing a cross-section of Chinese society that encompasses diverse age groups, occupations, and regions. As a platform frequently used for public discourse and rapid information sharing, Weibo serves as a valuable resource for capturing real-time public opinion on emerging issues, including the societal impacts of new technologies like AI. The specific case examined in this study is China's first lawsuit addressing AI-generated voice infringement, filed on April 23, 2024. This lawsuit, which remained a trending topic on Weibo until May 13 (Figure 2), provides a timely and pertinent example for analyzing how Chinese consumers interpret and respond to the potential legal and ethical challenges associated with AI technologies. By focusing on 10,447 Weibo posts from this time - authored by a user base that is 64.3% female with an average age of 25 - this study captures a wide range of authentic consumer perspectives on AI infringement issues.

Figure 3 underscores the regional diversity of the dataset, suggesting that this legal event offers a valuable lens through which to examine a broad cross-section of Chinese public sentiment on AI-related IP disputes. Regional fixed effects were not included in the regression analysis, as the study's focus lies in individual-level social capital rather than regional variation. Controlling for regional dummies risked absorbing meaningful variation in social network structures and masking nationally relevant patterns. Additionally, the event unfolded on widely accessible social media platforms, ensuring broad and near-simultaneous exposure across regions. We also refrained from subdividing the sample into high- and low-value regions to avoid introducing arbitrary thresholds and to maintain analytical focus on the relationship between social capital and public perceptions in a digitally interconnected society.

-------- Insert Figures 2 and 3 about here --------

The dataset is composed of three key parts, with the first focusing on consumer demographics. Gender (0 for male, 1 for female) is included because prior research has indicated that gender differences may influence social capital formation and engagement behaviors (Aldasoro, Armantier, Doerr, Gambacorta, and Oliviero, 2024), potentially shaping attitudes toward AI-related IP infringement. Age is considered as a proxy for generational influences on social media usage and perceptions of technological and legal issues. Education (0 for lower, 1 for undergraduate or higher) is incorporated to capture the role of cognitive resources and awareness in interpreting and reacting to AI-related IP issues. Employment status (0 for unemployed, 1 for employed) reflects varying levels of access to professional networks, which could enhance the understanding and valuation of intellectual property rights (cf. Grassini and Koivisto, 2024).

The second part focuses on platform-specific variables that provide a more detailed understanding of consumers' social media engagement and its relation to social capital. Platform membership tenure, measured in days, is included to assess how long-standing exposure to social media ecosystems shapes consumer attitudes and knowledge about digital rights. Account level serves as an indicator of social influence and prestige within the platform community, potentially affecting how others perceive and respond to their opinions. Personal information authentication (0 for not authenticated, 1 for authenticated) is considered important as verified accounts may signal credibility and increase their influence within social networks. The number of posts reflects engagement intensity, while thread visibility, measured by the duration of involvement in discussions (in days), indicates sustained participation in relevant conversations. Lastly, the numbers of subscriptions and subscribers represent out-tie and in-tie network capital, respectively, highlighting the breadth of connections a user maintains and their audience reach - both of which are crucial for understanding the dynamics of social capital in shaping attitudes toward AI-related IP infringement.

Third, we analyze the content of consumers' Weibo posts to examine their perceptions of China's first AI-generated voice infringement lawsuit. This analysis includes two key aspects: consumers' attitudes, categorized as 0 for neutral or positive and 1 for negative, and the presence of financial perceptions of AI, determined by whether the posts include finance-related content (marked as 0 for related and 1 for not). To extract and classify this information, machine learning techniques were applied to the translated English versions of the posts. The design and implementation details of these techniques are outlined in the following sections.

3.2. Analysis of Attitudinal Expressions in Posts

We assess consumer attitudes by analyzing the sentiments expressed in their posts using BERT, a large language model (Ardekani et al., 2024; Huang, Wang, and Yang, 2023; Wei, Wu, and Chu, 2023). BERT is particularly well-suited for this research due to its ability to capture linguistic context bidirectionally, simultaneously considering both preceding and following words in a sentence. This contextual understanding is critical for interpreting detailed consumer attitudes, enabling BERT to detect subtle shifts in tone or sentiment that unidirectional models might overlook. For instance, unidirectional models like Generative Pre-trained Transformer (GPT: Budhwar et al., 2023), which process text in only one direction — either left-to-right or right-to-left — may miss the interplay between words that provides crucial contextual cues in complex language structures. Furthermore, BERT's architecture excels in handling token-level dependencies, making it particularly adept at analyzing longer texts where relationships between words, phrases, and sentences are essential for sentiment determination. This capability aligns well with the dataset of user-generated posts, often characterized by complex phrasing, idiomatic expressions, and implicit emotional tones, where traditional approaches like lexicon-based models (Muñoz and Iglesias, 2022), Support Vector Machines (SVM: Tanveer et al., 2022), or Naive Bayes (Miric, Jia, and Huang, 2023) struggle to manage such variability and ambiguity.

For this study, we initially trained a BERT model by fine-tuning on a dataset of 39,480 translated social media (Weibo) posts, categorized as positive (871), neutral (14,721), or negative (23,842) and spanning the years 2023 to 2024 (pseudocode is shown in Appendix A.1). Sentiments were labeled based on the emotional tone of the text, with positive posts expressing favorable emotions such as happiness or approval, neutral posts reflecting a balanced or indifferent tone, and negative posts conveying dissatisfaction, anger, or other adverse emotions. Posts with mixed sentiments or complex structures were examined carefully to assign the sentiment category that best captured their overall emotional intent. This comprehensive labeling process ensured consistency across the dataset and provided a robust foundation for fine-tuning the BERT model. The posts, with an average length of 263 characters, were input at the character level, reflecting the concise yet expressive nature of user-generated social media content. The dataset was divided into 31,585 entries for training, 3,948 for validation, and 3,947 for testing. The model achieved strong performance, with 95.4% accuracy on the training set and 93.3% on the test set. Additionally, BERT provided sentiment clarity through confidence scores ranging from 0 to 1, representing the probability that its sentiment predictions - positive, neutral, or negative - accurately reflected the underlying sentiment of the text. The high confidence scores, illustrated in Figure 4, emphasize the reliability of BERT's predictions.

-------- Insert Figure 4 about here --------

3.3. Analysis of Financial Perceptions Surrounding AI

We employed the FastTextRank algorithm (Liu et al., 2024) to assess the relevance of post content to financial domains, focusing on its effectiveness in capturing key concepts and phrases critical to our analysis (pseudocode is shown in Appendix A.2). FastTextRank is a graph-based summarization algorithm that uniquely integrates the strengths of FastText embeddings with the TextRank algorithm, providing a robust mechanism for extracting relevant terms and concepts from large and diverse text datasets. This approach excels in identifying relationships within textual data due to its capacity to leverage FastText embeddings, which capture semantic and syntactic similarities even for out-of-vocabulary terms and misspelled words. This feature is particularly advantageous in analyzing user-generated content, where spelling variations, abbreviations, and informal language are prevalent.

The algorithm was applied to a predefined list of 1,288 financial terms (e.g., loan, ledger, bankrupt), enabling evaluation of text relevance. FastTextRank's graph-based structure ensures that the importance of terms is contextually weighted based on their interconnections within the text. This capability makes it more appropriate than traditional methods, such as Term Frequency-Inverse Document Frequency (TF-IDF: Harrison, Josefy, Kalm, and Krause, 2023) or original TextRank

(Wang, Hsiao, and Chang, 2020), which may struggle to account for contextual depth and semantic details in large, unstructured datasets. Furthermore, its adaptability to domain-specific lexicons, such as financial terminology, enhances its precision compared to general-purpose NLP techniques.

By combining FastText embeddings with the graph-based TextRank algorithm, FastTextRank provides a balance of scalability and contextual accuracy, making it particularly suitable for our study's objective of evaluating financial field relevance in complex and varied post content.

3.4. Regression Analysis

This study examined attitudes toward AI-related IP infringement as the dependent variable, using a negative attitude as the reference category. The primary independent variables were the number of subscriptions and subscribers, representing users' social capital. Financial perception of AI was included as a moderating variable, capturing its potential influence on the relationship between social capital and attitudes. Control variables included gender, age, education, employment, platform membership tenure, account level, personal information authentication, number of posts, and thread visibility. A summary of all variables and their operational definitions is presented in Table 3.

-------- Insert Table 3 about here --------

Table 4 summarizes the key study variables, indicating that most users express neutral or positive attitudes toward AI-related IP infringement (mean = 0.367, where 1 = negative attitude). This prevailing tolerance highlights the importance of this study, which aims to investigate the social and financial factors underlying consumers' attitudes. Several variables — particularly the number of posts and the number of subscribers — exhibit extreme positive skewness and kurtosis, reflecting a small number of highly active or influential users. To address these non-normal distributions and reduce the influence of outliers, platform membership tenure, number of posts, number of subscriptions, and number of subscribers are log-transformed in subsequent analyses. These transformations help stabilize variance, normalize distributions, and improve the reliability of regression estimates.

Table 5 presents Spearman correlations, revealing significant associations between attitude and several key variables. Notably, the study's main independent variables — the number of subscriptions ($\rho = -0.033$, $p < 0.001$) and the number of subscribers ($\rho = 0.042$, $p < 0.001$) — are both significantly related to attitude, highlighting their empirical relevance for the later binary probit models. Financial perception is also significantly related to attitude ($\rho = -0.225$, $p < 0.001$), though the direction of this relationship is not theoretically central, as financial perception is modeled as a moderator rather than a direct predictor in the conceptual framework. Additional significant correlations with gender, age, account level, personal information authentication, and thread visibility further support the inclusion of these variables as controls in the later models.

Table 6 highlights group-level comparisons, showing that consumer attitudes toward AI-related IP infringement vary significantly across several key variables examined in this study. Users with negative attitudes differ meaningfully from those with neutral or positive attitudes across demographic, social, and contextual factors. Significant differences are observed in variables such as gender, platform engagement, account features, and financial perception. These results suggest that consumer attitudes are not uniform but are shaped by a combination of individual characteristics and online behaviors, supporting the study's focus on how social capital and financial context interact to influence perceptions of AI-related IP infringement.

-------- Insert Tables 4, 5, and 6 about here --------

Given the binary nature of the dependent variable, the observed variability and skewness in predictors, significant correlations, and notable group differences, binary probit regression is statistically appropriate for this analysis (for binary probit models in sentiment analysis, see Feng, Fu, and Shi, 2022). This method effectively models the probabilities of attitudes toward AI-related IP infringement, accounting for covariates and data characteristics. The regression model is specified as follows:

$$P(Y=1|X) = \Phi\Bigg(\beta_0 + \beta_1 Subscriptions + \beta_2 Subscribers + \beta_3 Financial\ Perception + \sum\nolimits_{\gamma_k} Covariates_k\Bigg)$$

where Φ is the cumulative distribution function of the standard normal distribution, Y represents the binary dependent variable, and β and γ_k denote the coefficients for independent variables and covariates, respectively.

4. RESULTS

4.1. Interpretation of the Effects of Social Capital

Table 7 presents a stepwise analysis of how social capital, financial perception of AI, and their interactions influence consumer attitudes toward AI-related IP infringement. The models build incrementally, starting with control variables, followed by the independent variables, and finally incorporating the moderator and interaction terms. In Models 1–3, control variables such as gender, age, education, and employment consistently show significant effects. Gender has a significant negative coefficient across models, indicating that women are more likely to hold negative attitudes toward AI-related IP infringement, possibly due to heightened ethical sensitivities or concerns about risks. Similarly, education and employment show positive coefficients, suggesting that individuals with higher education levels or stable employment are more likely to adopt neutral or positive attitudes. Platform-specific factors, such as membership tenure and account level, also shape attitudes significantly, highlighting the role of contextual engagement.

-------- Insert Table 7 about here --------

In Model 2, the number of subscriptions (out-tie social capital) exhibits a positive and significant coefficient, supporting H1. This indicates that consumers with broader networks are more likely to encounter diverse viewpoints, which contributes to balanced and optimistic perspectives on AI. In Model 3, the number of subscribers (in-tie social capital) has a weaker but still positive effect. When both out-tie and in-tie social capital are included in Model 4, the positive and significant influence of out-tie social capital persists, underscoring its dominant role in shaping attitudes. In contrast, the coefficient for in-tie social capital becomes nonsignificant, suggesting that the influence of trusted but narrower in-tie connections is overshadowed by the more dynamic impact of out-tie networks. These findings emphasize the relatively greater importance of out-tie social capital in fostering neutral or positive attitudes. While subscribers, representing trusted and passive connections, do affect attitudes, their impact is less pronounced and dynamic compared to out-tie networks. Thus, the results provide partial support for H2.

4.2. Interpretation of the Effects of Financial Perceptions of AI

The introduction of financial perception of AI as a moderator in Model 5 alters these relationships significantly. Financial perception (coded as 1 for non-finance-related posts) has a strong positive effect, indicating that posts unrelated to finance are associated with more neutral or positive attitudes. This result underscores the framing effect of financial discussions: finance-related posts tend to emphasize risks, ethical dilemmas, or economic consequences of AI, fostering caution or negativity. Non-finance-related posts shift the focus to broader benefits, promoting acceptance of AI's applications.

In Model 6, the inclusion of financial perception and interaction terms reveals more detailed dynamics. For out-tie social capital, the interaction with financial perception is significant and negative, supporting H3. This shows that financial framing tempers the positive influence of out-tie networks by narrowing their typically broad and diverse perspectives. Financial discussions may direct attention to risks or contentious issues, thereby reducing the optimism that out-tie connections often foster. Nevertheless, the direct coefficient for out-tie social capital remains positive, indicating that even with financial framing, broader networks still have a net positive effect on attitudes.

For in-tie social capital, the coefficient shifts from positive in earlier models (e.g., 0.036 in Model 3) to negative (-0.415) in Model 6. This reversal highlights how financial framing weakens the influence of in-tie networks and turns it negative. This suggests that trusted connections within in-tie networks may amplify concerns or skepticism about financial discussions, leading to shared doubts or heightened critiques of AI. Notably, the interaction term between financial perception and in-tie social capital contradicts H4, as financial framing appears to reinforce the alignment of subscribers with financial implications, fostering more neutral or positive attitudes in certain contexts. This reveals the complexity of how financial framing interacts with trusted relationships in shaping attitudes.

4.3. Robustness Check

Table 8 presents a robustness check for the moderation analysis in Model 6, utilizing logistic regression with bootstrapping and a sample size of 10,000 (for an example of using bootstrapping to assess the robustness of moderation analysis results: Healey and Hodgkinson, 2024). The results reaffirm the significant moderating effects of financial perception observed in Model 6 of Table 7. The coefficient for financial perception underscores its strong role in shaping attitudes, with finance-related posts fostering more negative views and non-finance-related posts encouraging more positive ones. The interaction effects align with the probit regression findings, strengthening the interpretation. The negative interaction between financial perception and subscriptions further supports H3, indicating that financial framing tempers the positive influence of out-tie social capital. Similarly, the negative interaction between financial perception and subscribers confirms that financial framing weakens the influence of in-tie social capital. However, this interaction does not fully capture how financial perception fundamentally alters the effects of in-tie social capital, including reversing its direction, and therefore does not change our general conclusion. Overall, the bootstrapping analysis validates the robustness of our findings and reinforces the reliability of the moderation effects observed.

-------- Insert Table 8 about here --------

4.4. Endogeneity Issue

While endogeneity (Hill et al., 2021) is a valid concern in observational research — particularly when examining the relationship between social structures and attitudinal outcomes — the design and context of the present study substantially mitigate its potential impact. The focal event, China's first AI-generated voice infringement lawsuit, functions as a quasi-natural experiment due to its exogenous, unanticipated nature. As such, it is unlikely that social media users' prior attitudes influenced their exposure to or engagement with the event. Furthermore, the independent variables — measures of in-tie and out-tie social capital — are derived from pre-existing network configurations that temporally precede users' reactions, thereby reducing the plausibility of reverse causality. Although it is not possible to entirely eliminate the risk of omitted variable bias or self-selection effects, the use of large-scale, organic social media data offers additional robustness by capturing unsolicited, real-time public sentiment. Thus, while acknowledging that endogeneity cannot be wholly ruled out, the study's methodological design and event-driven context substantially constrain its influence, allowing for a credible interpretation of the observed associations.

5. DISCUSSION

5.1. Empirical Contributions

Our study highlights the complex interplay between social capital, financial perception, and consumer attitudes toward AI-related IP infringement. Out-tie social capital, characterized by broad and dynamic connections such as social media subscriptions, consistently fosters neutral or positive attitudes, even when financial framing is introduced. These networks weaken negative sentiments by exposing individuals to diverse perspectives, creating a buffering effect against skepticism. Conversely, in-tie social capital, rooted in close and trusted networks like subscribers or followers, begins with a positive influence but reverses when financial perception is introduced. Financial framing intensifies concerns or skepticism within these trusted circles, amplifying ethical critiques or perceived risks. This reversal underscores how financial contexts complicate the influence of in-tie networks, highlighting the power of trust to heighten sensitivity to ethical and financial considerations.

Financial perception moderates these dynamics by shaping the effects of social capital through the framing of AI-related discussions. Non-finance-related posts, which shift attention away from contentious issues like costs and risks, encourage acceptance by reinforcing the positive influence of out-tie networks and maintaining trust in in-tie networks. In contrast, finance-related framing tempers the positive influence of out-tie networks and weakens — or even reverses — the effect of in-tie networks as trusted groups amplify financial and ethical concerns. These findings emphasize the critical role of framing in AI-related discourse, showing how it profoundly shapes the interaction between social capital and consumer attitudes. By clarifying these mechanisms, our study offers valuable insights into navigating consumer perceptions and fostering informed discussions around AI adoption.

5.2. Theoretical Contributions

Our study contributes to social capital theory (e.g., Brennecke et al., 2024) from two key perspectives: how consumers' social capital shapes their perceptions of new technologies, and how it influences the development of IPR protection in the era of technologies like AI. First, our findings deepen social capital theory by demonstrating how the structure and function of social networks influence consumer perceptions of new technologies. Out-tie social capital fosters openness and cognitive flexibility by exposing consumers to diverse perspectives, reducing the psychological barriers to accepting novel technologies like AI. This suggests that out-tie networks play a critical role in mitigating uncertainty and facilitating positive engagement with innovation. Conversely, in-tie social capital highlights a paradox of trust: while trusted relationships initially encourage acceptance, they also heighten sensitivity to contextual factors, such as financial framing, which can shift attitudes toward skepticism or concern. This dual role of trust within in-tie networks extends social capital theory by emphasizing how contextual cues interact with network structure to shape consumer perceptions in more complex ways than previously understood.

Second, our study advances social capital theory by theorizing its influence on the collective acceptance and critique of IPR (Appel et al., 2023) in the AI era. Out-tie networks, with their ability to deliver diverse viewpoints, theoretically function as engines for normative diffusion, promoting broader societal acceptance of IPR as essential to technological progress. In contrast, in-tie networks provide a localized space for ethical deliberation, where trusted relationships amplify scrutiny and moral evaluation of IPR practices. This dynamic illustrates how different forms of social capital drive distinct processes of normative engagement: out-tie networks encourage widespread alignment with IPR frameworks, while in-tie networks foster critical discourse that can challenge or refine these norms. By linking these mechanisms to the evolving technological landscape, our study enriches social capital theory with insights into how network structures shape societal responses to IPR in the context of rapid innovation.

5.3. Contributions to Practice

Building on the empirical and theoretical contributions of this study, these insights offer practical guidance for navigating the challenges of IPR protection, ethical AI development (cf. Figueroa-Armijos et al., 2024), and global collaboration in the AI era.

First, our study provides actionable insights into fostering IPR protection in the rapidly evolving AI landscape. The findings underscore the importance of leveraging out-tie social capital — such as diverse and expansive social media networks — to promote widespread understanding and acceptance of IPR frameworks. These networks allow the dissemination of information about the benefits of IPR protection for innovation while addressing potential misconceptions. At the same time, attention must be given to in-tie networks, as their capacity for trust and critical scrutiny can surface ethical concerns. By engaging with these concerns transparently and addressing financial implications directly, stakeholders can foster an appropriate and constructive approach that aligns societal values with IPR policies in AI.

Second, the study highlights the detailed role of social capital in shaping consumer attitudes toward AI-related ethical dilemmas, offering practical implications for ethical AI development. Out-tie networks can be harnessed to diffuse positive narratives and reduce resistance to AI technologies, while in-tie networks should be engaged to address specific concerns related to trust and ethical implications. Developers and organizations can strategically frame discussions — moving beyond financial considerations to emphasize societal benefits and ethical safeguards — to sustain trust across these network types. This approach, while potentially mitigating polarized attitudes, may inadvertently lead to risks of infringement if critical ethical and financial concerns are overlooked in the process.

Third, the study's focus on AI-related IP issues in China offers valuable lessons for global stakeholders navigating similar challenges. China's unique interplay of social capital and consumer perceptions illustrates the importance of understanding local network dynamics and cultural attitudes when addressing IPR concerns. Applying these insights globally suggests the need for tailored approaches that respect regional differences in social capital structures (Xiao and Anderson, 2022) while promoting universal principles of ethical innovation and robust IPR frameworks. This contextual sensitivity can enhance global cooperation and support harmonized responses to the ethical and legal challenges of AI, ensuring that lessons from one context — such as China's approach to AI-related IP lawsuits — contribute to a more inclusive and informed global perspective.

5.4. Methodological Contributions

This study provides a valuable methodological contribution by demonstrating how LLMs, such as BERT, can be effectively integrated with complementary technologies like FastTextRank to analyze complex datasets. The integration showcases a robust framework where BERT's bidirectional contextual understanding is utilized to capture detailed consumer attitudes (cf. Huang et al., 2023), while FastTextRank identifies domain-specific content, such as financial terminology, with precision. This combination exemplifies how advanced NLP tools can work synergistically to handle the unique challenges posed by large, unstructured, and multilingual datasets like user-generated social media content.

This methodological contribution is significant for the development of LLMs in interdisciplinary research. By illustrating how BERT's contextual strengths can be augmented with domain-specific tools like FastTextRank, the study provides a replicable example for applying LLMs to fields beyond their traditional use cases. For instance, in finance, where textual data often involves subtle sentiment shifts and specialized terminology, such integrative approaches can enhance analytical depth and accuracy. More broadly, the framework underscores the importance of leveraging the unique strengths of different NLP technologies, thus advancing interdisciplinary innovations that address complex, real-world problems with greater precision and scalability.

5.5. Limitations and Future Directions

This study offers valuable contributions but also highlights limitations that open avenues for further research. First, focusing on out-tie and in-tie networks provides insights but simplifies the complexity of real-world social structures (Brennecke et al., 2024). Advanced network modeling, such as multi-level or multiplex analysis, could capture the roles of core and peripheral members more effectively, revealing their influence on consumer perceptions of AI-related IP infringement.

Second, consumer attitudes toward AI-related IP infringement evolve alongside advancements in AI technologies, exhibiting reciprocal dynamics with social capital. These mutual influences require longitudinal studies to explore how evolving norms, trust, and technologies reshape network structures and perceptions over time.

Third, the integration of BERT and FastTextRank for sentiment analysis and financial framing detection demonstrates methodological strength but does not fully capitalize on the advanced capabilities of LLMs. Future studies could leverage LLMs to track temporal sentiment shifts, identify causal relationships, and perform cross-contextual analyses, providing deeper insights into how network structures and content framing influence consumer attitudes. Expanding LLM applications in this way would enhance the understanding of discourse dynamics and sentiment evolution across diverse social and cultural settings.

Addressing these limitations will refine the findings and support more robust frameworks for managing public perception in the AI era.

6. CONCLUSIONS

This study provides a detailed understanding of how social capital influences consumer attitudes toward AI-related IP infringement, emphasizing the interplay between network structures, financial perceptions, and ethical considerations. Out-tie social capital, characterized by broad and diverse connections, fosters openness and mitigates resistance to AI technologies, particularly when discussions are framed outside of financial contexts. In-tie social capital, rooted in trust and close relationships, reveals a paradox: while initially promoting acceptance, it amplifies skepticism when financial framing introduces concerns about costs and risks. These findings underscore the dynamic and context-dependent nature of social capital in shaping consumer and financial perceptions of emerging technologies. By building on these findings, firms can more deeply understand the value creation routes for their increased investment in AI development.

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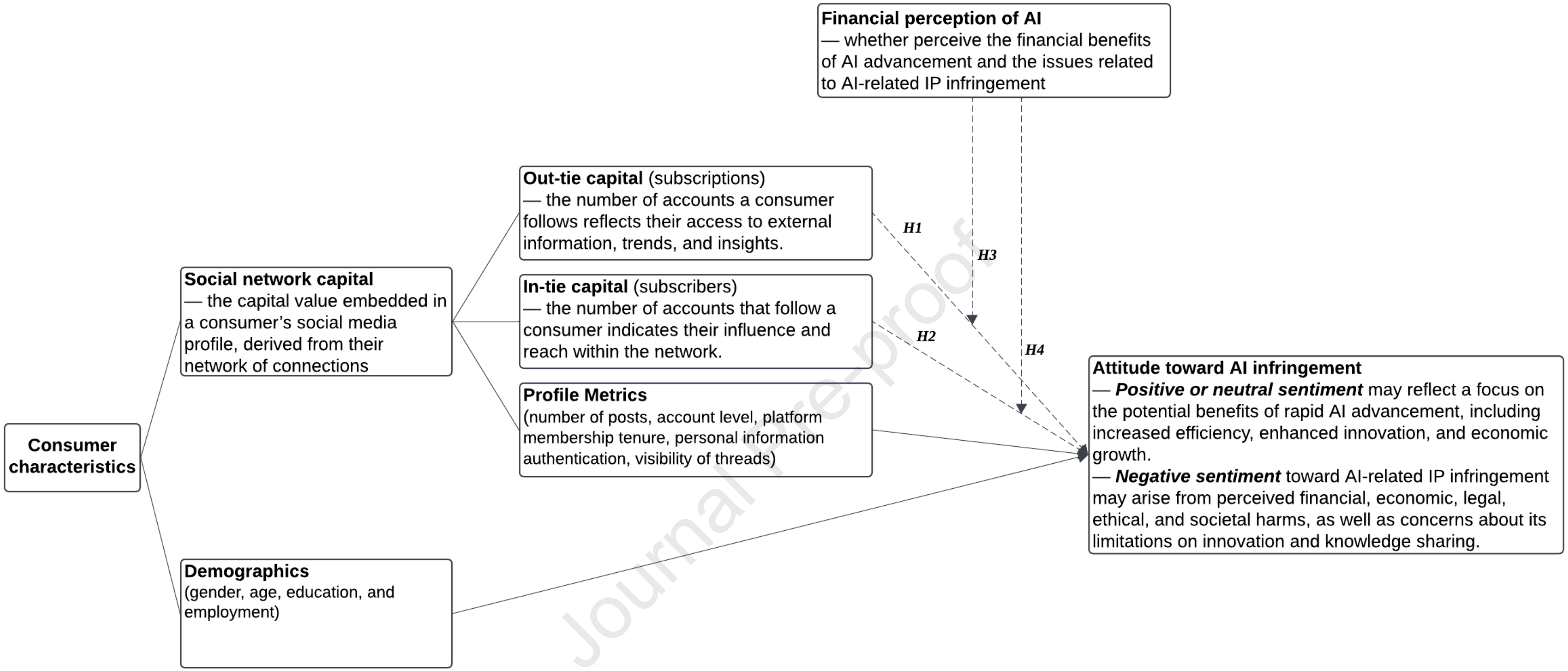

Figure 1. Relationships between consumer characteristics, financial perceptions of AI, and attitudes toward AI-related IP infringement

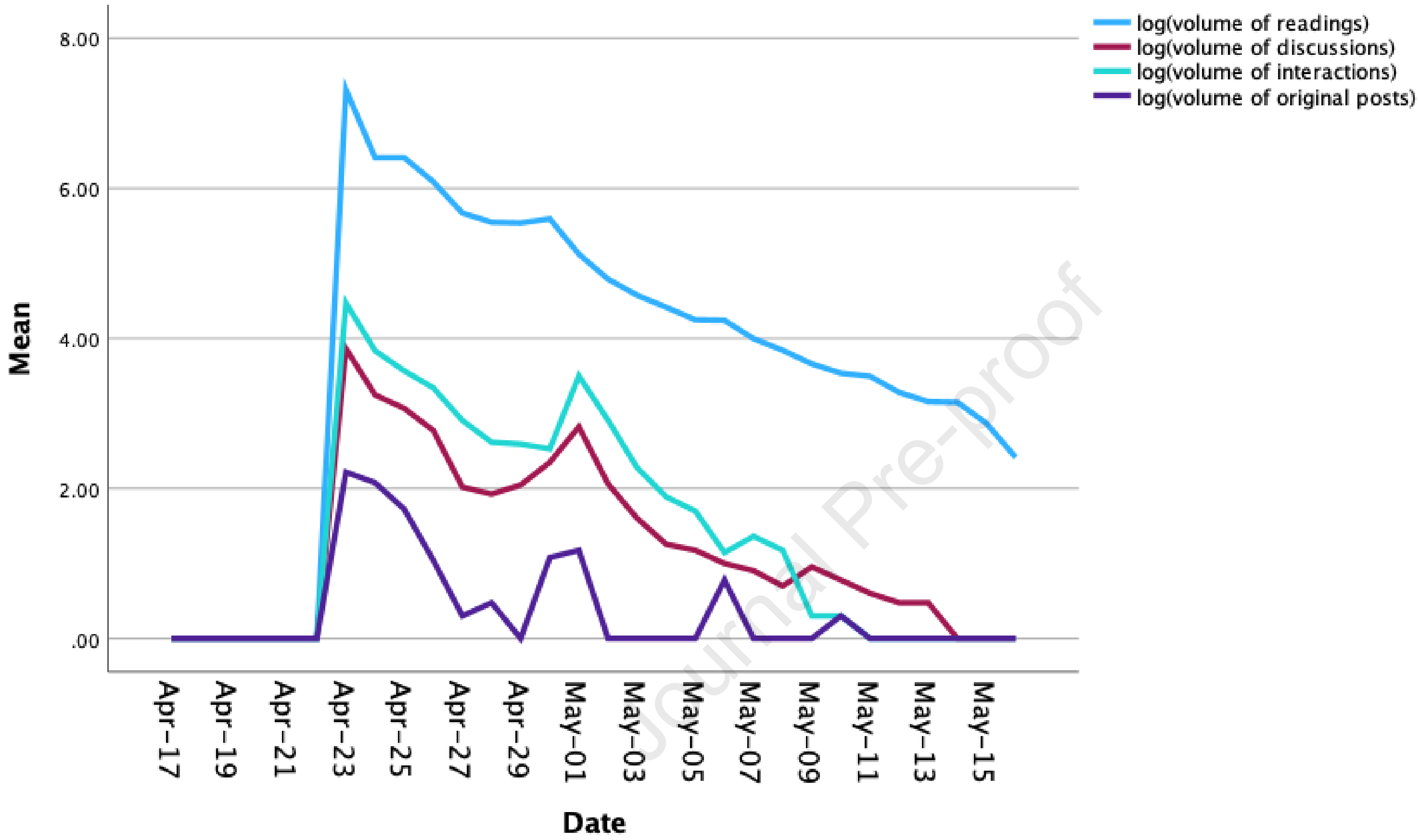

Figure 2. Topic popularity

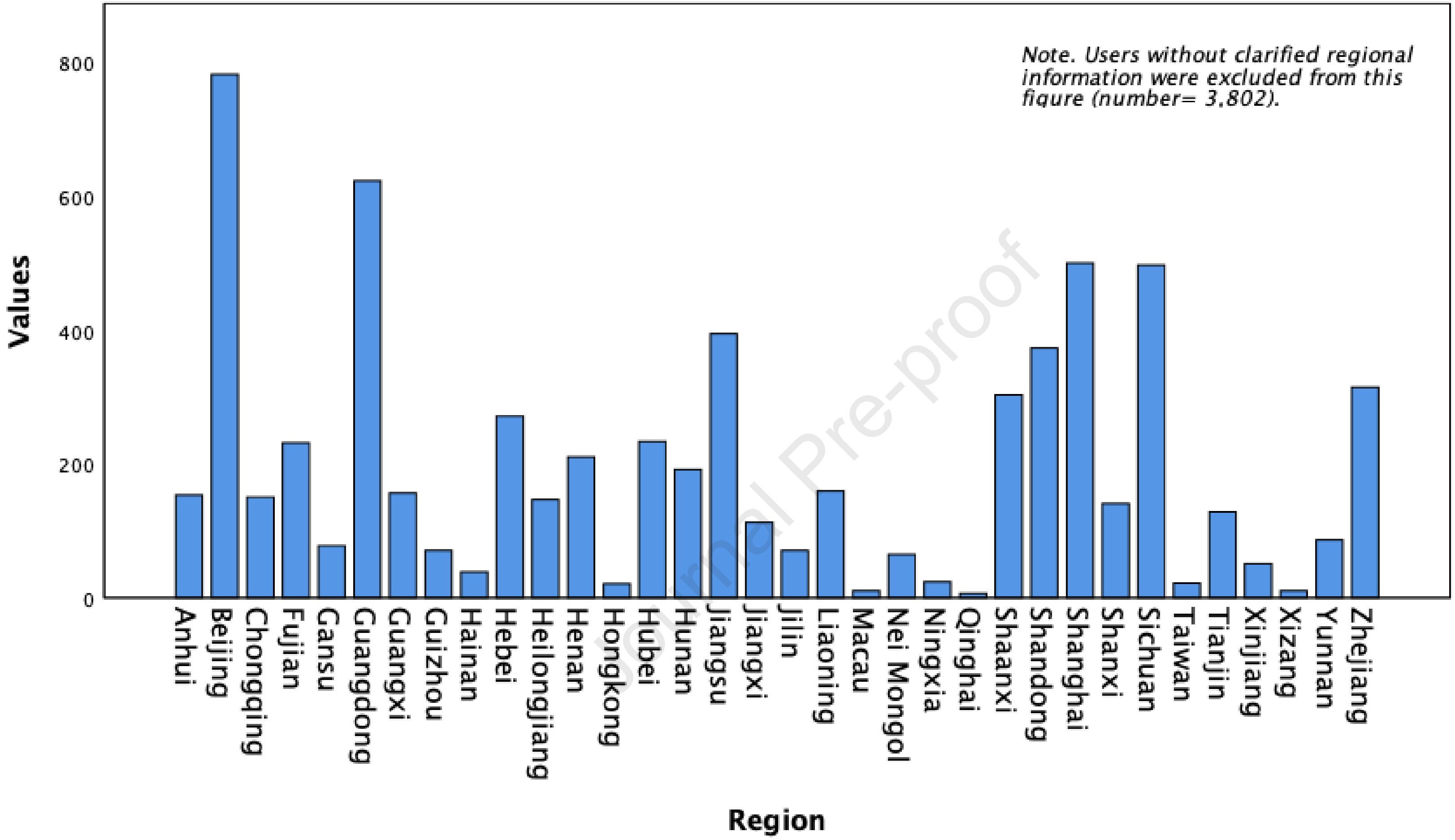

Figure 3. Region frequency

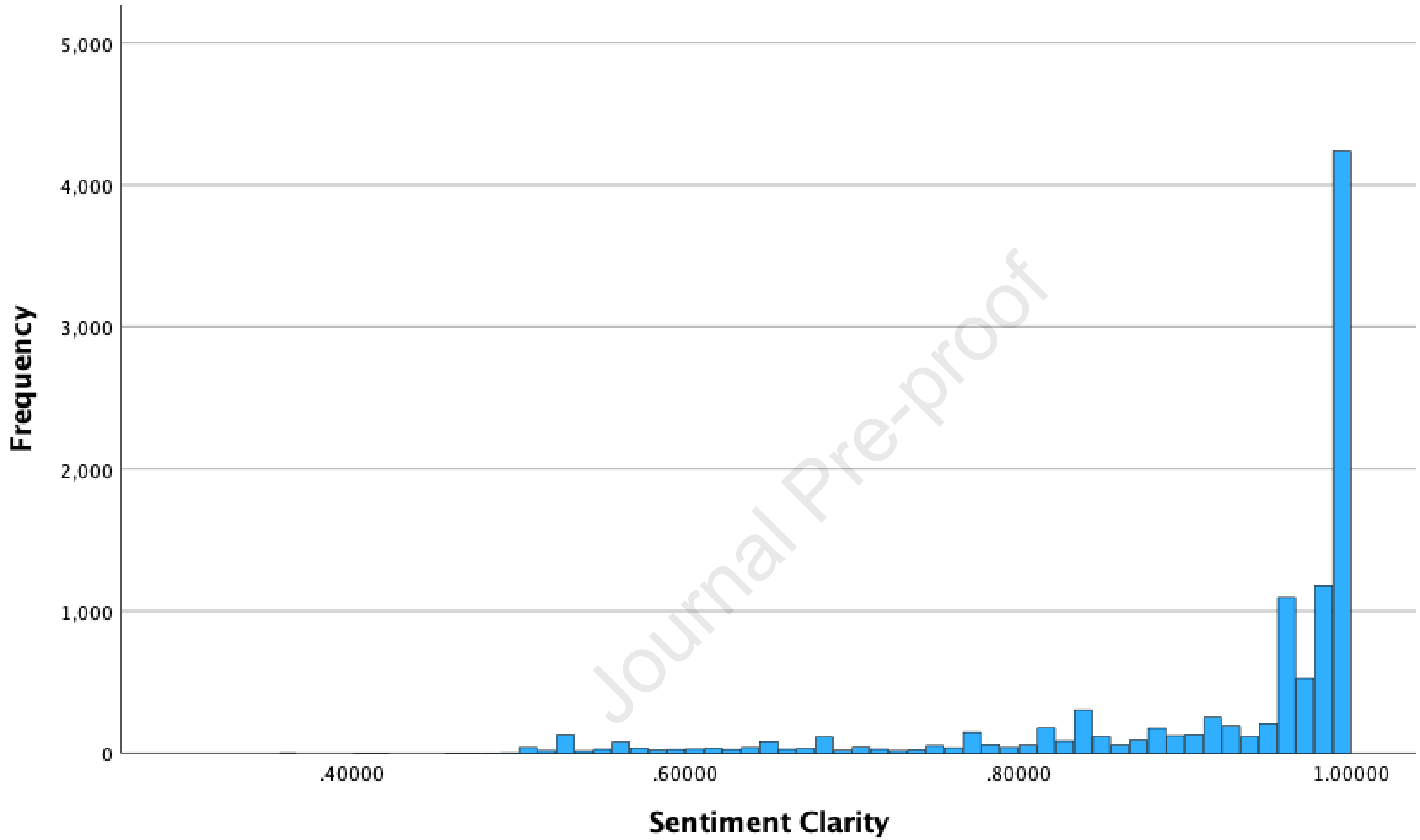

Figure 4. Clarity distribution

Table 1. Benefits of AI advancements on social capital, risks of AI-related IP infringement, and potential solutions

AI TECHNOLOGY	BENEFITS	POTENTIAL INFRINGEMENT	PROPOSED SOLUTION
AI-Generated Content Creation	Strengthens in-tie social capital by captivating followers with visually appealing and diverse content. Grows out-tie capital through a range of compelling posts that extend reach and encourage cross-platform virality, raising creator visibility and expanding network impact (e.g., Saffarizadeh et al., 2024).	AI-generated content may unintentionally incorporate copyrighted materials, exposing creators and platforms to IP infringement claims (e.g., Samuelson, 2023). For smaller creators with limited legal resources, this risk is particularly challenging. Platforms face potential liability from cumulative copyright violations if not addressed.	Advocate for standardized licensing frameworks for training datasets, adopt digital watermarking (Chen et al., 2024) for AI outputs, and support transparent industry norms for IP-compliant data sourcing.
Automated Personalization and Recommendations	Deepens in-tie capital by delivering highly personalized content (Kumar et al., 2024) that resonates with followers, boosting engagement and retention. Facilitates out-tie capital by suggesting relevant connections, enabling users to grow their networks and enhancing the platform's overall value.	Using proprietary user data in training models without proper licensing or explicit consent can lead to IP infringement, posing risks under privacy and IP laws like General Data Protection Regulation (GDPR: Evans, Hajli, and Nisar, 2023). Non-compliance risks costly penalties, especially for platforms operating in multiple jurisdictions with stringent data protection rules.	Develop IP-compliant, consent-driven data use policies for AI, enforce anonymization protocols (Majeed and Lee, 2020) for third-party data, and conduct routine compliance checks to safeguard against infringement liabilities.

Table 1. (*continued*)

AI-Driven Audience and Content Analytics	Supports in-tie capital growth by helping creators optimize content strategies for follower retention and higher engagement (e.g., Saffarizadeh et al., 2024). Fuels out-tie capital through detailed analytics that reveal potential growth opportunities and audience insights, providing value for creators and advertisers alike.	Analyzing user engagement data for AI model training without obtaining clear permissions can violate user rights and infringe on IP agreements, potentially resulting in legal action and financial repercussions (e.g., Appel et al., 2023). Misuse of data risks damaging platform credibility and eroding user trust, affecting long-term profitability.	Introduce IP-compliant agreements for the use of engagement data, anonymize data (Ni et al., 2022) for AI purposes, and conduct regular IP audits to monitor and reduce risks related to unauthorized data use.
Synthetic Media and Digital Influencers	Builds in-tie capital by developing unique digital personas (e.g., Salminen et al., 2024) that strongly connect with niche audiences and attract loyal followers. Promotes out-tie capital through cross-platform collaborations, expanding reach and creating monetization avenues for both creators and brands.	Digital personas resembling real individuals may infringe on copyright, trademark, or publicity rights. Unauthorized use of a person's likeness could lead to IP infringement lawsuits (e.g., Appel et al., 2023), especially impacting high-profile figures and exposing platforms to significant financial and reputational harm.	Establish robust guidelines for digital persona creation, enforce identity verification protocols (Ahmad, 2024), and require consent for likeness use to mitigate risks associated with unauthorized representations and IP-related claims.

Table 2. Potential harms of AI-related IP infringement across different dimensions

CATEGORY	POINT	EXPLANATION
Financial (Economic) harm (e.g., Appel et al., 2023; Samuelson, 2023; Samuelson, 2024)	Market distortion	AI infringement enables firms to reduce costs unfairly, creating competitive disadvantages for those adhering to IP protections.
	Innovation deterrence	The creation and distribution of AI-generated content that infringes on copyrights discourage original creators and data providers from innovating, as their works risk being used without permission or reward.
	Revenue losses	Violations of IPR in AI deprive original creators and data owners of potential revenue, negatively impacting creative and data-centric industries.
	Investor risk	Companies using unauthorized data or creating copyright-infringing AI content face financial risks from potential legal challenges, which may deter investors due to concerns about legal and regulatory liabilities.
	Depreciation of IP value	AI infringement reduces the perceived value of IP assets, damaging sectors reliant on proprietary data and creative works for valuation.
	Increased legal costs	Legal expenses from defending against IPR claims can consume resources needed for further AI development and innovation.
Legal harm (e.g., Appel et al., 2023; Samuelson, 2024; Teli et al., 2024)	Legal penalties	Firms involved in IP infringement in AI risk facing lawsuits, fines, and penalties that may restrict their market access.
	Regulatory uncertainty	The rapid pace of AI developments, especially in content generation, has outpaced regulatory frameworks, making it challenging for firms to comply with evolving IP-related legal requirements.
	Jurisdictional conflicts	Variations in IPR laws between countries create jurisdictional challenges, making it difficult to enforce AI-related IPR protections consistently across borders.

Table 2. (*continued*)

Ethical and societal harm (e.g., Du and Xie, 2021; Hajli et al., 2022; Yan et al., 2024)	Public trust erosion	Public trust in AI can erode when unauthorized data or IP-infringing content is used, as users may question the ethical standards of AI developers and the technology's respect for copyright laws.
	Exploitation of creators	AI that replicates or builds upon original works without permission, either through unauthorized data use or copyright-violating content generation, exploits creators and diminishes recognition of their contributions.
	Reputational damage	Companies found using unauthorized data or creating infringing AI content risk lasting reputational harm, facing consumer and industry backlash for violating IPR standards.
Innovation and knowledge sharing constraints (e.g., Appel et al., 2023; Grimaldi et al., 2021; Samuelson, 2024)	Barrier to open innovation	The risk of IP infringement in AI discourages collaborative innovation, as organizations are reluctant to share data or content that could be misappropriated in AI training or generation.
	Data access restrictions	To prevent potential IP misuse, data and content providers may restrict access, limiting the resources available for developing transparent and ethically-driven AI solutions.
	Hindrance to standardization	Concerns about IP infringement hinder the development of widely accepted standards for ethical data use and content generation in AI, making it harder for AI systems to be compatible and consistent across different industries.

Table 3. Summary of Regression Variables and Proxies

Variable Type	Variable Name	Proxy
Dependent Variable	Attitude toward AI-related IP infringement	Binary variable: 0 = Neutral/Positive, 1 = Negative
Independent Variables	Out-tie Social Capital	Number of subscriptions
	In-tie Social Capital	Number of subscribers
Moderator	Financial Perception of AI	Binary variable: 0 = Finance-related content present, 1 = Not finance-related
Covariates	Gender	Binary variable: 0 = Male, 1 = Female
	Age	Continuous variable (in years)
	Education	Binary variable: 0 = Lower education, 1 = Undergraduate or higher
	Employment	Binary variable: 0 = Unemployed, 1 = Employed
	Platform Membership Tenure	Continuous variable: Number of days since account creation
	Account Level	Ordinal variable indicating account prestige/social influence level
	Personal Information Authentication	Binary variable: 0 = Not authenticated, 1 = Authenticated
	Number of Posts	Continuous variable: Total number of posts authored by user
	Thread Visibility	Continuous variable: Duration of participation in discussions (in days)

This table presents the dependent variables, independent variables, moderators, and covariates, along with their corresponding proxies used in the measurement and regression analysis.

Table 4. Descriptive statistics of variables

	Mean	SD	Skewness	Kurtosis
Attitude	0.367	0.482	0.550	-1.697
Gender	0.643	0.479	-0.598	-1.642
Age	25.667	14.735	4.196	23.319
Education	0.093	0.291	2.790	5.788
Employment	0.104	0.305	2.592	4.721
Platform membership tenure	2,858.579	1,449.382	-0.151	-1.054
Account level	2.108	2.410	1.035	-0.330
Personal information authentication	0.244	0.430	1.186	-0.592
Number of posts	15,200.597	32,005.870	9.883	285.925
Thread visibility	2.587	2.746	2.147	4.543
Number of subscriptions	739.329	1,128.797	5.824	60.481
Number of subscribers	246,704.326	6,394,345.061	35.898	1,320.633
Financial perception	0.936	0.244	-3.568	10.736

This table presents descriptive statistics for all relevant variables. The dataset includes a total of 10,447 observations, comprising 667 finance-related posts and 9,780 non-finance-related posts. Sentiment analysis categorizes the posts as 5,845 neutral, 764 positive, and 3,838 negative. Standard deviations (SD) are reported for all variables. To enhance statistical analysis, variables such as platform membership tenure, number of posts, number of subscriptions, and number of subscribers are log-transformed in subsequent analyses.

Table 5. Spearman correlations

	1	2	3	4	5	6	7	8	9	10	11	12
1. Attitude												
2. Gender	0.071***											
3. Age	-0.049***	-0.149***										
4. Education	-0.018	-0.012	0.121***									
5. Employment	-0.007	-0.100**	0.120***	0.242***								
6. Platform membership tenure	0.003	-0.170***	0.536***	0.124***	0.187***							
7. Account level	0.106***	0.135***	0.091***	0.089***	0.124***	0.200***						
8. Personal information authentication	0.109***	-0.213***	0.084***	0.061***	0.236***	0.251***	0.157***					
9. Number of posts	0.018	-0.203***	0.318***	0.034***	0.179***	0.476***	0.237***	0.410***				
10. Thread visibility	0.035***	0.055***	-0.110***	-0.027**	-0.009	-0.100***	-0.028**	0.059***	-0.119***			
11. Number of subscriptions	-0.033***	-0.011	0.181***	0.098***	0.146***	0.358***	0.264***	0.151***	0.419***	-0.090***		
12. Number of subscribers	0.042***	-0.197***	0.314***	0.140***	0.275***	0.572***	0.361***	0.597***	0.613***	-0.073***	0.437***	
13. Financial perception	-0.225***	0.102***	-0.012	0.042***	-0.039***	-0.052***	0.004	-0.165***	-0.135***	-0.028**	0.009	-0.131***

This table presents the results of examining monotonic relationships between variables, with all coefficients calculated using Spearman's rank correlation. $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$.

Table 6. Comparison of consumer characteristics based on their different attitudes toward AI-related IP infringement

Characteristics	**Attitude**	**Mean**	**SD**	***t***
Gender	Positive (neutral)	0.617	0.486	-7.229***
	Negative	0.687	0.463	
Age	Positive (neutral)	26.085	15.169	3.808***
	Negative	24.947	13.930	
Education	Positive (neutral)	0.097	0.296	1.832***
	Negative	0.086	0.281	
Employment	Positive (neutral)	0.105	0.307	0.711
	Negative	0.101	0.301	
Platform membership tenure	Positive (neutral)	3.350	0.370	-3.542***
	Negative	3.375	0.317	
Account level	Positive (neutral)	1.931	2.336	-9.930***
	Negative	2.414	2.504	
Personal information authentication	Positive (neutral)	0.209	0.406	-11.197***
	Negative	0.306	0.461	
Number of posts	Positive (neutral)	3.469	0.961	-1.729
	Negative	3.503	0.950	
Thread visibility	Positive (neutral)	2.611	2.837	1.153***
	Negative	2.546	2.581	
Number of subscriptions	Positive (neutral)	2.581	0.574	2.142***
	Negative	2.557	0.492	
Number of subscribers	Positive (neutral)	2.201	1.300	-4.752
	Negative	2.329	1.365	
Financial perception	Positive (neutral)	0.978	0.146	23.593***
	Negative	0.864	0.342	

This table compares the characteristics of consumers based on their attitudes toward AI-related IP infringement. Significance levels are denoted as follows: $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$, with two-tailed tests applied. SD stands for standard deviations. The *p*-value for the number of subscribers is 0.071, indicating significance at the 0.1 level, though it is relatively weaker compared to other results.

Table 7. Binary probit regression analysis examining consumer attitudes toward AI infringement

	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5	MODEL 6
Gender	-0.228***	-0.241***	-0.220***	-0.236***	-0.271***	-0.279***
	(0.028)	(0.028)	(0.028)	(0.028)	(0.029)	(0.029)
Age	0.003***	0.003***	0.003***	0.003***	0.003***	0.003**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education	0.120**	0.107*	0.115*	0.105*	0.054	0.037
	(0.045)	(0.045)	(0.045)	(0.045)	(0.046)	(0.046)
Employment	0.123**	0.111*	0.111*	0.105*	0.112*	0.116*
	(0.044)	(0.044)	(0.044)	(0.044)	(0.045)	(0.046)
Platform membership tenure	-0.107*	-0.158***	-0.132**	-0.169***	-0.201***	-0.206***
	(0.041)	(0.042)	(0.043)	(0.043)	(0.044)	(0.044)
Account level	-0.044***	-0.047***	-0.046***	-0.048***	-0.055***	-0.057***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Personal information	-0.403***	-0.395***	-0.452***	-0.422***	-0.400***	-0.389***
authentication	(0.032)	(0.032)	(0.038)	(0.039)	(0.039)	(0.040)
Number of posts	0.066***	0.041*	0.052**	0.035*	0.062***	0.056**
	(0.016)	(0.016)	(0.017)	(0.017)	(0.017)	(0.017)
Thread visibility	0.011*	0.011*	0.011*	0.011*	0.018***	0.014**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Number of subscriptions		0.139***		0.131***	0.095***	0.663***
		(0.027)		(0.027)	(0.028)	(0.122)
Number of subscribers			0.036*	0.020	0.054***	-0.415***
			(0.015)	(0.015)	(0.016)	(0.052)
Financial perception					1.237***	1.431***
					(0.057)	(0.289)

Table 7. (*continued*)

Financial perception × Number of subscriptions						-0.598*** (0.124)
Financial perception × Number of subscribers						0.507*** (0.051)
Constant	0.687*** (0.132)	0.598*** (0.133)	0.750*** (0.135)	0.638*** (0.136)	-0.470** (0.148)	-0.611* (0.307)
LR χ^2	323.303***	349.661***	328.988***	351.271***	870.587***	1,000.254***
Observations	10,447	10,447	10,447	10,447	10,447	10,447

This table presents the regression results examining the impacts of consumers' social capital on their attitudes toward AI infringement. The dependent variable is attitudes toward AI-related IP infringement, with negative attitudes as the reference category. The independent variables are the numbers of subscriptions (out-ties) and subscribers (in-ties), with financial perceptions of AI serving as the moderator. Control variables include consumers' gender, age, education, employment status, platform membership duration, account level, personal information verification, number of posts, and thread visibility. Model 1 includes only the control variables. Models 2 and 3 separately assess the impacts of subscriptions and subscribers, respectively. Model 4 evaluates the combined effect of both primary independent variables. Model 5 incorporates the influence of consumers' financial perceptions of AI. Finally, Model 6 examines the moderating effect of these financial perceptions on the relationship between social capital and attitudes toward AI-related IP infringement. Significance levels are denoted as follows: $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$. Standard errors are reported in parentheses.

Table 8. Bootstrapping analysis

	Coefficient	Bias	SE	95% Confidence Interval	
				Lower	Upper
Gender	0.466***	0.002	0.048	0.373	0.560
Age	-0.005**	0.000	0.002	-0.008	-0.002
Education	-0.064	-0.001	0.077	-0.215	0.086
Employment	-0.189*	-0.001	0.079	-0.346	-0.038
Platform membership tenure	0.340***	0.000	0.072	0.199	0.483
Account level	0.093***	0.000	0.010	0.075	0.112
Personal information authentication	0.633***	0.000	0.068	0.502	0.766
Number of posts	-0.091**	0.000	0.029	-0.148	-0.034
Post visibility	-0.024**	0.000	0.008	-0.039	-0.008
Number of subscriptions	-1.188***	-0.015	0.221	-1.656	-0.780
Number of subscribers	0.755***	0.009	0.097	0.591	0.966
Financial perception	-2.485***	-0.025	0.502	-3.546	-1.572
Financial perception × Number of subscriptions	1.084***	0.015	0.225	0.668	1.557
Financial perception × Number of subscribers	-0.910***	-0.009	0.096	-1.121	-0.743
Constant	1.142*	0.024	0.532	0.152	2.245

This table presents the results of the robustness check for the moderating effect of consumers' financial perceptions of AI benefits and risks on the relationship between their social capital and attitudes toward AI-related IP infringement. Logistic regression with bootstrapping was employed, using a sample size of 10,000 for the bootstrapping procedure. Standard errors (SE) are reported. Significance levels are indicated as follows: $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$.

APPENDIX A

A.1. Pseudocode for sentiment analysis

```
def train(config, model, train_iter, dev_iter, test_iter):
    # Initialize start time
    start_time = time.time()

    # Set the model to training mode
    model.train()

    # Get model parameters
    param_optimizer = list(model.named_parameters())

    # Define parameters not subject to weight decay
    no_decay = ['bias', 'LayerNorm.bias', 'LayerNorm.weight']

    # Group parameters into those with and without weight decay
    optimizer_grouped_parameters = [
        {'params': [p for n, p in param_optimizer if not any(nd in n for nd in no_decay)],
'weight_decay': 0.01},
        {'params': [p for n, p in param_optimizer if any(nd in n for nd in no_decay)],
'weight_decay': 0.0}
    ]

    # Initialize the optimizer based on configuration
    optimizer = AdamW(optimizer_grouped_parameters, lr=config.learning_rate)

    # Initialize total batch count
    total_batch = 0

    # Set the best validation loss to infinity
    dev_best_loss = float('inf')

    # Initialize the count of batches since last improvement
    last_improve = 0

    # Set the improvement flag to False
    flag = False

    # Loop over epochs
    for epoch in range(1, config.num_epochs + 1):
        print(f'Epoch [{epoch}/{config.num_epochs}]')
```

```
for trains, labels in train_iter:
    # Get model outputs
    outputs = model(trains)

    # Clear gradients
    model.zero_grad()

    # Compute loss
    loss = loss_fn(outputs, labels)

    # Backpropagate the loss
    loss.backward()

    # Update parameters
    optimizer.step()

    # Every 100 batches, evaluate and print metrics
    if total_batch % 100 == 0:
        # Compute and print training accuracy
        train_acc = compute_accuracy(outputs, labels)
        print(f'Training Accuracy: {train_acc:.4f}')

        # Evaluate on the validation set
        dev_acc, dev_loss = evaluate(model, dev_iter)
        print(f'Validation Accuracy: {dev_acc:.4f}, Validation Loss: {dev_loss:.4f}')

        # Check if the validation loss has improved
        if dev_loss < dev_best_loss:
            dev_best_loss = dev_loss
            # Save model state
            torch.save(model.state_dict(), config.save_path)
            last_improve = total_batch
            improve = '*'
        else:
            improve = ''

        # Print current iteration info
        print(f'Iter: {total_batch:>6}, Train Loss: {loss.item():>6.4f}, Train Acc:
{train_acc:>6.2%}, Val Loss: {dev_loss:>6.4f}, Val Acc: {dev_acc:>6.2%}, Time:
{get_time_dif(start_time)} {improve}')

    model.train()
```

```
            total_batch += 1

            # Check for early stopping
            if total_batch - last_improve > config.require_improvement:
                print("No improvement for a long time, stopping training...")
                flag = True
                break

        if flag:
            break

    # Evaluate the model on the test set
    test(config, model, test_iter)


class Model(nn.Module):
    def __init__(self, config):
        super(Model, self).__init__()
        # Load pre-trained BERT model
        self.bert = BertModel.from_pretrained(config.bert_path)

        # Set gradients for BERT parameters
        for param in self.bert.parameters():
            param.requires_grad = True

        # Initialize fully connected layer
        self.fc = nn.Linear(config.hidden_size, config.num_classes)

    def forward(self, x):
        # Get input sentence
        context = x[0]

        # Get padding mask
        mask = x[2]

        # Process input through BERT, exclude all encoded layers
        _, pooled = self.bert(context, attention_mask=mask,
output_all_encoded_layers=False)

        # Pass BERT output through the fully connected layer
        out = self.fc(pooled)

        # Return the final output
```

```
    return out
```

A.2. Pseudocode for classifying post content relevance to finance

```
class FastTextRank4Word:
    def __init__(self, use_stopword=False, stop_words_file=None, max_iter=100,
tol=0.0001, window=2):
        # Initialize instance variables
        self.__use_stopword = use_stopword
        self.__max_iter = max_iter
        self.__tol = tol
        self.__window = window
        # Initialize the stop words set as an empty set
        self.__stop_words = set()
        # Set the default stop words file path
        self.__stop_words_file = self.get_default_stop_words_file()
        # If a custom stop words file is provided
        if stop_words_file:
            self.__stop_words_file = stop_words_file
        # If using stop words
        if use_stopword:
            with open(self.__stop_words_file, 'r') as file:
                for line in file:
                    self.__stop_words.add(line.strip())
        # Set NumPy floating-point error warnings
        np.seterr(all='warn')

    def get_default_stop_words_file(self):
        # Get the directory of the current script
        d = os.path.dirname(os.path.abspath(__file__))
        # Return the full path to the default stop words file
        return os.path.join(d, 'stopwords.txt')

    def build_worddict(self, sents):
        # Build mappings for word to index, index to word, and count total words
        word_index = {}
        index_word = {}
        words_number = 0
        for word_list in sents:
            for word in word_list:
                if word not in word_index:
                    word_index[word] = words_number
                    index_word[words_number] = word
                    words_number += 1
```

```
        # Return the word to index mapping, index to word mapping, and total word
count
        return word_index, index_word, words_number

    def build_word_graph(self, sents, words_number, word_index, window=2):
        # Construct the word graph where nodes are words and edges are co-
occurrence within the window
        graph = [[0.0 for _ in range(words_number)] for _ in range(words_number)]
        for word_list in sents:
            for i in range(len(word_list)):
                for j in range(i+1, i+window):
                    if j >= len(word_list):
                        break
                    w1, w2 = word_list[i], word_list[j]
                    if w1 in word_index and w2 in word_index:
                        index1, index2 = word_index[w1], word_index[w2]
                        graph[index1][index2] += 1.0
                        graph[index2][index1] += 1.0
        # Return the constructed word graph
        return graph

    def summarize(self, text, n):
        # Process the input text and generate a summary
        text = text.replace('\n', '').replace('\r', '')
        text = util.as_text(text)
        sents = util.cut_sentences(text)
        sents, word_list = util.psegcut_filter_words(sents, self.__stop_words,
self.__use_stopword)
        word_index, index_word, words_number = self.build_worddict(word_list)
        graph = self.build_word_graph(word_list, words_number, word_index,
self.__window)
        scores = util.weight_map_rank(graph, self.__max_iter, self.__tol)
        top_words = nlargest(n, scores.items(), key=lambda x: x[1])
        sent_index = [index for index, score in top_words]
        summary = [index_word[i] for i in sent_index[:min(n, len(sent_index))]]
        return summary
```

Credit Author Statement

All authors have contributed substantially to the development of this manuscript. Their contributions are as follows:

- **Tian Wei**: Conceptualization, Methodology, Data Curation, Formal Analysis, Writing – Original Draft, Writing – Review & Editing
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- **Michael Dowling**: Supervision, Project Administration, Writing – Review & Editing, Manuscript Structuring, Rewriting
- **Aref Mahdavi Ardekani**: Supervision, Project Administration, Writing – Review & Editing, Manuscript Structuring, Rewriting

All authors have reviewed and approved the final manuscript.