ARTIFICIAL INTELLIGENCE AND FINTECH: ENHANCING FINANCIAL WELL-BEING THROUGH IT MINDFULNESS

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ABSTRACT

This study examines the antecedents and outcomes of using mobile fintech applications, including mobile banking, mobile payments, mobile transfer and mobile financial money management tools. This paper examines the antecedents (i.e. financial education and financial literacy) and outcomes (i.e. desirable financial behaviors and financial well-being) of the utilization of mobile fintech. Using data from the 2018 National Financial Capability Study and structural equation modelling techniques, this study provides empirical evidence to show significant direct and indirect relationships among these factors. Findings: The structural equation modelling results revealed that financial education was positively associated with both financial literacy and mobile fintech utilization. Interestingly, financial literacy was negatively associated with mobile fintech utilization and served as a negative mediator between financial education and mobile fintech utilization, while it positively correlated with desirable financial behaviors, enhancing financial well-being. Utilization of mobile fintech was negatively associated with desirable financial behaviors and indirectly and negatively associated with financial well-being. The alternative model highlighted a direct and negative association between mobile fintech usage and financial well-being, and a direct positive association between financial literacy and financial well-being. Originality/value: This study makes contributions to the literature on financial well-being by examining pathways of antecedents and outcomes of mobile fintech utilization. The findings provide new insights into the rapid evolution of mobile fintech innovations and provide important policy and practical implications.

This study explores the transformative role of Artificial Intelligence (AI), IT Mindfulness, Technological and financial self-efficacy in FinTech, emphasizing its impact on financial well-being and the integration of Technophobia and privacy risk into technology adoption. By leveraging the Unified Theory of Acceptance and Use of Technology (UTAUT), the research examines how AI-powered FinTech services enhance user trust, empower decision-making, and promote financial resilience. The

study highlights IT Mindfulness as a critical factor influencing technological and financial self-efficacy, fostering better Task-Technology Fit. It underscores the potential of AI-driven FinTech solutions to advance financial inclusion and well-being, offering novel insights into the interplay of technology, trust, and user behavior in the digital age.

Keywords: Financial technologies, Fintech, Financial wellbeing, Mindfulness, Technological self-efficacy, Technophobia

1. INTRODUCTION

In recent years, financial services across the globe have experienced significant transformations due to technological advancements, giving rise to FinTech, the combination of technology and financial services (Abis et al., 2024; Alt et al., 2024; Goldstein et al., 2019; Milian et al., 2019). Consequently, the rise of FinTech along with Artificial intelligence has been a game-changer, dramatically transforming the financial services landscape, and has emerged as a key driver in enhancing consumers' financial well-being by offering greater accessibility, efficiency, and personalized financial solutions through the use of AI intelligence (Jourdan et al., 2023; Lagna & Ravishankar, 2022). Notably, these fintech services significantly provide not only several reasonable, innovative, and secure services like digital payments, mobile payment platforms, peer-to-peer payment platforms, contactless payments, and digital wallets but also integrate emerging AI technologies such as Robo advisors, chatbots, blockchain, neo banks, lending platforms, crowdfunding, wealth management as well digital insurance platforms(Al-Sharafi et al., 2022; Friedman & Ormiston, 2022; Gao et al., 2020; Hornuf & Haddad, 2019). Further, FinTech apps with AI can support consumers in making better financial decisions by providing them with user-friendly apps that aid in increasing financial awareness and knowledge, which can lead to improved outcomes(Belanche et al., 2019; B. Z. Zhang et al., 2021). Moreover, AI intelligence is not only revolutionizing and redefining the banking sector by elevating customer satisfaction and offering highly customized services(Barone et al., 2024; Priya & Sharma, 2023). But, Despite the increasing integration of AI in FinTech, there is limited empirical evidence on how AI-driven features influence user adoption behavior and decision-making effect on Users' views on the practicality, simplicity, and enjoyment of adopting financial technology(Rita Gonçalves, 2023; Mogaji & Nguyen, 2022; Sheth et al., 2022). Addressing this gap could provide insights into the psychological and behavioral drivers of FinTech adoption.

Drastically, FinTech has rapidly emerged as a significant driver of financial well-being, financial inclusion, and socio-economic progress, attracting widespread global interest (Dzogbenuku et al., 2022; Gafoor & Amilan, 2024). Moreover, the future of financial services in this new era hinges on the seamless integration of fintech innovations and a dedicated emphasis on enhancing financial wellness for their users(Zhang & Fan, 2024). Due to these advancements, users are now seeking more practical services that can be accessed anytime and anywhere, while also being more

cost-effective(Gonçalves et al., 2023). In addition, FinTech is empowering individuals by democratizing access to financial services, enhancing financial inclusion, and offering personalized financial planning (Hasan et al., 2021; A. Kumar et al., 2022; Tigges et al., 2024). Specifically, the increasing demand for quicker and more accurate information through digital tools is successfully addressed by leading FinTech firms that go beyond simply seeking superior tools and services reflecting fintech ability to broader aspiration to cultivate and sustain a sense of financial well-being(J. Kumar et al., 2023) Consequently, financial well-being is often regarded as the ultimate outcome of financial technologies which significantly impact people's physical and emotional health, as well as their ability to engage meaningfully with the world around(Gafoor & Amilan, 2024). Nonetheless, A considerable gap still exists.in the literature regarding the precise definition of financial well-being and the specific ways in which fintech products and services contribute to its attainment(Zhang & Fan, 2024). There is limited or no research focusing on how these innovations specifically contribute to enhancing consumer financial well-being(Kanungo & Gupta, 2021).

Alongside, mindfulness has also been shown to positively affect financial decision-making and stress management (Schomburgk & Hoffmann, 2023; Wu et al., 2022).While existing studies indicate that IT mindfulness can improve overall well-being and decision-making capabilities, there is a notable research gap concerning how IT mindfulness interacts with specific psychological barriers like technophobia, which often hinders the adoption of digital financial technologies(Sun et al., 2016). Moreover, the potential of IT mindfulness to enhance financial and technological self-efficacy empowering individuals to feel more confident and capable of managing their finances through the FinTech platform remains underexplored in current literature. This gap is significant given that financial self-efficacy has been identified as a critical factor in the effective assimilation and sustained utilization of FinTech services. (Roh et al., 2022; Shiau et al., 2020). The interplay between IT mindfulness, technophobia, and financial self-efficacy and technological self-efficacy could offer valuable insights into the behavioral intentions of users toward FinTech, driven by digital transformations and technological advancements(Shiau et al., 2020). Addressing this gap could provide a profound comprehension of how IT mindfulness practices can be harnessed to mitigate psychological impediments and there is an absence of holistic frameworks that incorporate these psychological dimensions to more precisely forecast consumer adoption behavior. (Al-Qudah et al., 2024; Rizvi et al., 2024).

Privacy risk remains an underexplored factor in FinTech adoption, particularly its influence on behavioral intention and factors like performance expectancy, effort expectancy, and hedonic motivation ((Jafri et al., 2024).While FinTech services offer convenience and efficiency, privacy and data security concerns can deter continued use((Alalwan et al., 2024) The moderating role of privacy risk, especially in shaping user expectations and behavioral intentions, has received limited attention (Bajunaied et al., 2023; Roh et al., 2022) Addressing this gap can deepen understanding of FinTech adoption barriers and provide insights to enhance

financial inclusion and well-being through solutions that tackle privacy concerns alongside psychological barriers (Sampat,et al., 2024).

India's FinTech sector is on a rapid growth trajectory, with its market size anticipated to soar from $584 billion in 2022 to around $1.5 trillion by 2025 (Statista, 2022). This expansion is supported by India's young and increasingly economically active population—68% under 35 years and 55% in the 20-59 age group in 2020, with the latter expected to reach 56% by 2025 (Ministry of Statistics and Programme Implementation, 2020). Furthermore, India demonstrates an exceptional FinTech adoption rate of 87%, eclipsing the global average of 64% and ranking second only to China. (Ernst & Young, 2021). The digital payments sector also shows robust growth, with transaction values projected to more than triple by 2025, up from 72 billion transactions valued at INR 1,744 trillion ($24 trillion) in FY21-22 (RBI). This growth is driven by the sector's smartphone-native design, 24/7 availability, and cost-effective features, which are particularly appealing to Millennials and Gen Z.

FinTech's value lies in its simplicity, offering transparent, cost-effective financial services. As the industry evolves, academic interest in consumer adoption has grown, but gaps persist in understanding adoption outcomes. While research on FinTech-customer dynamics is emerging, comprehensive studies remain limited. This study bridges these gaps by proposing an AI-driven FinTech adoption model based on the Unified Theory of Acceptance and Use of Technology (UTAUT). It examines how AI intelligence, IT mindfulness, technological self-efficacy, and financial self-efficacy influence users' intentions to adopt FinTech. Additionally, it explores broader outcomes, including financial inclusion and well-being, to reveal how FinTech enhances financial health and generates socio-economic benefits. By analyzing both determinants and outcomes, this research fills a critical void in the literature, offering fresh insights into FinTech's transformative potential.

RQ1 To what extent does Artificial Intelligence serve as a transformative force in driving and structuring the adoption paradigms of FinTech innovations?

RQ2 How does FinTech enhance financial well-being, and what factors most influence this impact?

RQ3 How do IT mindfulness, technological and financial self-efficacy affect the adoption of financial technologies? And how does technophobia influence the usage of these technologies?

This study fills a critical gap in the literature by exploring novel factors influencing consumer adoption of financial technology (FinTech) and the outcomes of such adoption. Research on FinTech adoption in India remains limited, investigating the impact of technological factors (e.g., Artificial Intelligence [AI], Task Technology Fit) and psychological factors (e.g., IT mindfulness, technological self-efficacy).

A key contribution of this research is its focus on AI intelligence, a factor often overlooked in prior studies. By including AI as a determinant, this study aims to

deepen the understanding of its role in shaping consumer intentions to adopt FinTech. Furthermore, it highlights the importance of IT mindfulness, a relatively underexplored factor, in enhancing FinTech adoption while mitigating technophobia's adverse effects. Notably, existing research has not examined IT mindfulness as a mechanism to reduce technophobia's influence on adoption intentions.

2. CONCEPTUAL FRAMEWORK

2.1 FinTech

The term "FinTech," a blend of "finance" and "technology," first appeared in academic literature in 1972 but gained significant attention post-2008 global financial crisis, which accelerated transformations in the financial sector. These transformations included enhanced security, flexibility, and access to financial information (Goldstein et al., 2019; Gomber et al., 2017).FinTech refers to the integration of technologies such as cloud computing, mobile internet, blockchain, and big data with financial services (Gomber et al., 2017). By 2021, global investments in FinTech had surpassed $98 billion, with India's sector valued at $50–60 billion, expected to reach $150 billion by 2025 (NASSCOM & BCG, 2021).Research on FinTech significantly expanded after 2014, particularly on innovations like alternative finance, cryptocurrencies, blockchain, AI, and associated risks and regulatory challenges. Sub-sectors such as payments, RegTech, InsurTech, crowdfunding, mobile trading, Robo-advisory, and blockchain have attracted interest from startups, investors, and regulators(Belanche et al., 2019). However, there is ongoing debate about whether FinTech is a disruptive or innovative technology(Leong et al., 2017)

FinTech encompasses a diverse ecosystem involving firms specializing in wealth management, payments, lending, and crowdfunding, alongside technology providers offering solutions like big data analytics and cloud computing (Lee & Shin, 2018). Government bodies, regulators, and policymakers play a crucial role, along with established financial institutions and customers, both individual and corporate. India has become a global leader in adopting financial technologies, driven by government initiatives like the UPI (Unified Payments Interface). Despite the growing body of research on FinTech, there is limited exploration of the factors influencing its adoption, with a need for further investigation into the barriers, facilitators, and outcomes of FinTech adoption. Studying FinTech adoption, especially in regions like India, is vital for promoting financial inclusion and understanding consumer behavior. It also helps assess the impact of technological advancements and government policies on economic growth.

2.2. LITERATURE REVIEW AND THEORETICAL UNDERPINNING

a) Unified Theory of Acceptance and Use of Technology (UTAUT2)

This study explores consumers' intention to adopt FinTech, drawing from established models of technology adoption. Over the years, several theoretical frameworks have emerged to understand the acceptance of information technology, including the Diffusion of Innovation (Rogers, 1995), the Theory of Planned Behavior (Ajzen, 1991) and the Technology Acceptance Model (TAM) ((Davis, 1989). The most integrative model is the Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh and Davis (2000; 2003) and later expanded to UTAUT2 (Venkatesh et al., 2012) which integrates various adoption frameworks and has been widely applied in research on technologies like FinTech, blockchain, and AI (Bommer et al., 2022).UTAUT2 has demonstrated strong explanatory capability in understanding consumer intentions toward innovations in banking technology (Mogaji & Nguyen, 2024; Oliveira et al., 2014b; Patil et al., 2020).This model posits that an individual's behavioral intention to adopt technology is influenced by factors such as performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit. For FinTech adoption, constructs such as performance expectancy, effort expectancy, and hedonic motivation are particularly relevant, as these reflect the core motivations for users who value ease of use, functionality, and enjoyable experiences.

Given the critical role of government initiatives like UPI in driving FinTech adoption in India, UTAUT2 is a fitting framework for understanding how these contextual factors influence consumer behavior. However, UTAUT2 has been critiqued for omitting factors such as privacy, security, and risk, which are pivotal in FinTech adoption. To address this gap, this study incorporates privacy risk, technophobia, and IT mindfulness as additional constructs. By integrating these variables, the study aims to provide a comprehensive framework for understanding the adoption and usage of FinTech products and services.

b) Task Technology Fit (TTF)

Task Technology Fit (TTF) theory, developed by Goodhue and Thompson (1995), posits that technology adoption is influenced by the extent to which the technology fits the tasks users need to accomplish. TTF is particularly relevant when assessing how technology can enhance performance by facilitating task completion. This model has been widely used in studies on mobile banking adoption (Oliveira et al., 2014a) and other technology adoption contexts ((Hassan et al., 2020; Pillai & Sivathanu, 2020). It highlights that users are more likely to adopt a technology if it improves task performance and aligns well with task characteristics.

TTF offers a rational perspective on how FinTech can optimize financial tasks, depending on both the task's inherent characteristics and the technology's capabilities. This model is particularly useful for understanding FinTech adoption because it emphasizes the practical benefits of technology in accomplishing financial tasks, such as managing finances or making payments. By integrating TTF with UTAUT2, this study seeks to provide a comprehensive understanding of FinTech adoption, combining both task-related and user-related factors.

Despite the prevalence of FinTech services, there is limited research on actual usage, with most studies focusing on behavioral intention or continuous usage intention. This study aims to bridge this gap by exploring the connection between behavioral intention and actual use of FinTech, a relationship that has often been neglected. By analyzing both behavioral intention and actual usage, the study will offer insights into the broader adoption process.

c) Psychological Factors and Moderators

In addition to the core constructs from UTAUT2 and TTF, this study incorporates psychological factors such as technological self-efficacy, financial self-efficacy, and IT mindfulness, which influence how users perceive and interact with FinTech. These factors are particularly relevant in the context of FinTech adoption, as they shape users' confidence in using technology and their ability to manage financial tasks effectively. Moreover, technophobia, the fear or anxiety surrounding new technologies, is examined as a moderating factor in the adoption process. Technophobia has often been studied in relation to computer technology but less so in the context of FinTech, making it a valuable addition to this research.

Privacy risk is another important moderator in FinTech adoption. Given the concerns about data security and privacy in digital finance, understanding how privacy risks affect users' decisions to adopt FinTech is critical. This study will investigate the role of privacy risk in shaping users' behavioral intention and actual usage of FinTech products and services.

The research will explore how AI, IT mindfulness, self-efficacy, technophobia, and privacy risk interact to influence the adoption of FinTech, focusing on their impact on financial well-being and financial inclusion. The goal is to provide a comprehensive theoretical and empirical foundation for understanding FinTech adoption, which will help stakeholders like businesses, policymakers, and investors identify opportunities and challenges in the rapidly growing FinTech sector.

2.3. HYPOTHESIS DEVELOPMENT

2.3.1 Artificial Intelligence (AI)

Artificial Intelligence (AI) plays a pivotal role in enhancing the performance expectancy of financial technologies, particularly within FinTech applications. AI functionalities, such as predictive analytics, tailored financial advice, and automated decision-making, have significantly improved the efficiency, accuracy, and reliability of FinTech platforms ((Ashta & Herrmann, 2021)(Huang et al., 2024) As users interact with AI-powered systems, they experience improved task performance with reduced effort, thereby increasing their performance expectancy. AI's ability to automate complex processes and provide real-time financial insights boosts user confidence in the technology's ability to meet their financial goals (Belanche et al., 2019; Huang et al., 2024) aligning with the Unified Theory of Acceptance and Use of Technology (UTAUT), where performance expectancy is a crucial factor in

technology adoption (Venkatesh et al., 2012). The integration of AI into FinTech not only reduces manual effort but also optimizes operations, fostering greater user satisfaction and encouraging sustained use. Research on Robo-advisors also highlights that perceived usefulness is key in shaping customer attitudes during early adoption stages (Ashta & Herrmann, 2021; Belanche et al., 2019). Furthermore, the use of AI in various financial services, such as fraud detection, trading forecasts, and risk modelling, introduces new challenges while enhancing operational effectiveness (Tschang & Almirall, 2021; van Esch et al., 2019) Studies also show that AI decisions, compared to human decisions, often lead to greater consumer satisfaction due to perceived impartiality (Gonçalves, 2023). Thus, we hypothesize that:

H1a: Artificial Intelligence (AI) in FinTech applications positively influences the performance expectancy of FinTech apps.

AI can also enhance effort expectancy by simplifying user interactions and automating routine financial tasks. AI-driven tools like chatbots, Robo-advisors, and personalized financial dashboards provide real-time guidance, reducing cognitive load and making financial processes more efficient (Hentzen et al., 2021; Sheth et al., 2022b) This ease-of-use increases users' perceptions of the effort required to manage finances. For instance, AI-enabled predictive analytics automate investment decisions and optimize financial planning, positively influencing the perception of system efficiency (Hentzen et al., 2022). This leads to greater adoption of AI-based financial services. Accordingly, we propose the following hypothesis:

H1b: Artificial Intelligence (AI) in FinTech applications positively influences the effort expectancy of FinTech apps.

AI also enhances hedonic motivation by creating more personalized and engaging experiences. Tools like virtual assistants and personalized investment recommendations make financial interactions more enjoyable and user-friendly. AI transforms traditionally complex financial management tasks into satisfying experiences, amplifying users' intrinsic enjoyment((Baptista & Oliveira, 2016). Additionally, AI-driven gamification elements further increase enjoyment by turning financial tasks into rewarding experiences (Venkatesh et al., 2012). Based on this, we hypothesize:

H1c: Artificial Intelligence (AI) in FinTech technologies positively influences the hedonic motivation of users to engage with FinTech apps.

AI can also enhance IT mindfulness by fostering conscious and intentional interaction with technology. AI-driven systems offer personalized, context-aware prompts and real-time feedback that encourage users to remain aware of their technological actions (Ioannou et al., n.d.; Oeldorf-Hirsch & Chen, 2022; Wu et al., 2022). Adaptive AI interfaces guide users through decision-making, helping them stay focused and avoid mindless interactions ((Schomburgk & Hoffmann, 2023; Sun et al., 2016).Thus, we hypothesize:

H1d: AI intelligence in FinTech services positively influences users' IT mindfulness.

AI in FinTech can significantly boost financial self-efficacy by providing users with personalized insights, intelligent tools, and decision-support systems that simplify complex financial tasks. This empowers users to make informed decisions and increases their confidence in managing finances(Shiau et al., 2020). Similarly, technological self-efficacy is enhanced through AI's intuitive interfaces and personalized guidance, making FinTech platforms more user-friendly (Balakrishnan & Shuib, 2021)). Hence, we hypothesize:

H1e: AI intelligence in FinTech positively influences users' financial self-efficacy.

H1f: AI intelligence in FinTech positively influences users' technological self-efficacy.

2.3.2 Impact of IT Mindfulness

In the Western context, mindfulness is defined as "receptive attention to and awareness of present events and experiences" (Brown et al., 2018) and being in the present moment, paying attention without judgment ((Flavian et al., 2020). Mindful individuals tend to explore additional features of technology, leading to a deeper understanding of its capabilities, enhancing perceived usefulness and overall user adoption (Wu et al., 2022). In our study, we define performance expectancy as the belief users hold about the usefulness of FinTech applications. IT mindfulness enhances users' ability to evaluate the performance expectancy of financial technologies by encouraging intentional interactions with FinTech platforms. Mindful users are more aware of the features and functionalities that can improve their financial decision-making. This awareness enables users to better assess how effectively FinTech apps help them achieve their goals, such as convenience, accuracy, and efficiency. Therefore, IT mindfulness leads to a clearer understanding of the expected performance and benefits of using financial technologies. When users practice IT mindfulness, they are more likely to recognize how these tools can streamline financial tasks and ultimately help them meet their financial goals(Sun et al., 2016).Thus, we hypothesize:

H2a: IT mindfulness has a positive influence on users' performance expectancy of financial technologies.

A core aspect of technology adoption is ease of use, which reduces cognitive effort. Mindful users, by being more aware of their needs and how technology can meet those needs, are better positioned to assess the ease of use of technology (Spatola & Wudarczyk, 2021). As a result, IT mindfulness can enhance perceptions of the effectiveness of financial technologies. Thus, we hypothesize:

H2b: IT mindfulness has a positive influence on users' effort expectancy of financial technologies.

IT mindfulness also enhances hedonic motivation by fostering deeper engagement and enjoyment of technology. Mindful users are more aware of their emotions and experiences while interacting with digital platforms, which allows them to appreciate the positive aspects, such as the pleasure derived from seamless interactions and personalized features (Zhou, 2011). This heightened awareness increases users' motivation to engage with technology, as they find more enjoyment in their interactions (Hsu & Chiu, 2004) .Therefore, we hypothesize:

H2c: IT mindfulness positively influences users' hedonic motivation to use financial technologies.

Research indicates that IT mindfulness enhances users' engagement with technology, leading to increased technological self-efficacy (Sun et al., 2016). Mindful users tend to pay closer attention to technology's features and functionalities, improving their understanding of how to use these systems effectively(Thatcher et al., 2018).This deeper engagement reduces the cognitive load of learning new technologies and improves users' competence, boosting their confidence in navigating technological platforms. Consequently, we hypothesize:

H2d: IT mindfulness positively influences users' technological self-efficacy.

IT mindfulness also enhances financial self-efficacy by encouraging a more deliberate and focused approach to using FinTech. Mindful users are better able to explore FinTech features, leading to informed financial decisions and improved resource management (Mindra et al., 2017). Mindfulness helps reduce financial stress, aligns FinTech tools with personal financial goals, and promotes goal-oriented behavior, thereby increasing financial self-efficacy (Brown & Ryan, 2003). Additionally, mindful individuals are better equipped to manage complex decision-making environments, which further strengthens their financial confidence (Barber & Odean, 2013).Thus, we hypothesize:

H2e: IT mindfulness positively influences users' financial self-efficacy.

2.3.3 Technological Self-Efficacy and Financial Self-Efficacy

Financial self-efficacy and technological self-efficacy are important determinants of users' engagement with financial technologies. Individuals with high financial self-efficacy are more likely to use financial tools effectively, leading to better financial management ((Farrell et al., 2016). Similarly, technological self-efficacy influences how well users can navigate and use technology. Studies have shown that individuals confident in their technological abilities are more likely to effectively engage with complex systems (Compeau & Higgins, 2017) .Dhir et al. (2021) found that higher technological self-efficacy correlates with better satisfaction and engagement with digital financial platforms. The combination of financial and technological self-efficacy improves Task Technology Fit (TTF), contributing to more effective financial decision-making(Goodhue & Thompson, 1995).Thus, we hypothesize:

H3(a) Financial self-efficacy positively impacts Task Technology Fit (TTF).

H3(b) Technological self-efficacy positively impacts Task Technology Fit (TTF).

2.3.4 Performance Expectancy, Effort Expectancy, and Hedonic Motivation

Performance expectancy (PE) refers to the extent to which users believe technology will enhance their performance in specific tasks (Venkatesh et al., 2012). In FinTech, when users perceive that an app can improve financial management and decision-making, they are more likely to use it (Jadil et al., 2021). This aligns with Davis' (1989) findings on perceived usefulness and adoption intention. Thus, we propose:
H4a – Performance expectancy significantly drives the intention to use FinTech apps.

Effort expectancy is the ease of using a system (Venkatesh et al., 2003). In the context of FinTech, when users find apps easy to use, their intention to adopt increases (Senyo & Osabutey,2020).

H4b – Effort expectancy positively influences the intention to use FinTech apps.

Hedonic motivation, or the enjoyment derived from using technology, also plays a crucial role in adoption (Venkatesh et al., 2012). In FinTech, engaging, user-friendly apps lead to greater adoption (Ryu,2018). Therefore, we hypothesize:

H4c – Hedonic motivation significantly drives the intention to use FinTech apps.

2.3.5. Task Technology Fit (TTF)

TTF refers to how well a technology aligns with the tasks it is meant to support (Goodhue & Thompson, 1995). When a FinTech app fits users' financial goals, such as budgeting or investment tracking, they are more likely to use it (Parthiban & Adil, 2023). Therefore, we propose:

H5a –Task Technology Fit significantly drives the intention to use FinTech apps.

H5b – Task Technology Fit positively influences the actual usage of FinTech apps.

2.3.6 Behavioral Intention and Actual Usage

Behavioral intention predicts actual usage, particularly in technology adoption (Ajzen, 1991). Research has shown that higher intention leads to greater adoption ((Leong et al., 2017). In FinTech, users with strong intentions are more likely to use the service (Venkatesh et al., 2003). Therefore, we hypothesize:
H6 – Behavioral intention positively influences the actual usage of FinTech services.

2.3.7 Financial Well-Being

Financial well-being refers to the perception of being able to sustain desired living standards ((Brüggen et al., 2017). FinTech services, such as mobile banking and investment apps, have been shown to improve financial well-being by enhancing financial literacy, increasing savings, and fostering financial inclusion ((Mir & Bushra, 2024). Additionally, FinTech's user-friendly interfaces reduce financial stress (Dzogbenuku et al., 2022). As FinTech continues to evolve, understanding its impact on financial well-being is critical. We hypothesize:
H7 – The adoption and usage of FinTech services will positively impact individuals' financial well-being.

2.3.8. Financial Inclusion

Financial inclusion refers to access to affordable, safe financial services ((Varghese & Viswanathan, 2018). In India, initiatives like the Jan Dhan Yojana and mobile payment systems (e.g., Paytm, UPI) have significantly improved access to financial services, especially in rural areas(Schuetz & Venkatesh, 2020). Financial technologies drive inclusion by reducing transaction costs, enabling micro-lending, and improving financial literacy (Kim et al., 2018). We hypothesize:
H8a – The adoption and usage of FinTech services in India will positively impact financial inclusion.
H8b – Financial inclusion will positively impact financial well-being.

2.3.9. Technophobia

Technophobia, the fear or anxiety associated with using technology, moderates the relationship between behavioral intention and actual usage (Khasawneh, 2018). High technophobia can reduce the likelihood of adopting FinTech services, even with high behavioral intention ((Singh et al.,2020).Thus, we hypothesize:
H9 – Technophobia weakens the relationship between behavioral intention and actual usage of FinTech services.

2.3.10 Privacy Risk as a Moderator

Privacy concerns significantly affect individuals' willingness to adopt FinTech services. Perceived vulnerability to data breaches or unauthorized access reduces engagement with digital financial services (Roh et al., 2022).Studies suggest that privacy risk affects the adoption of FinTech (Ryu, 2018), but its moderating role in the relationship between performance expectancy, effort expectancy, and behavioral intention is underexplored. High privacy risk can diminish hedonic motivation, reducing behavioral intention (Putri et al., 2023). We propose:
H10a) The relationship between performance expectancy and behavioral intention is weakened by privacy risk.
H10b) The relationship between effort expectancy and behavioral intention is weakened by privacy risk.

H10c) The relationship between hedonic motivation and behavioral intention is weakened by privacy risk.

3.1. DATA COLLECTION

Sampling and Survey Method: The empirical data for this study were collected from 650 participants, with 469 valid responses, yielding a 51.6% response rate. The participants were selected based on their prior experience with FinTech services. To reach diverse generational cohorts, multiple outreach strategies were employed. For Generation X, you used LinkedIn, email, and community forums. Millennials were contacted via social media platforms (Facebook, Instagram), email, and offline surveys. Generation Z was primarily reached through social media channels such as TikTok, Snapchat, and educational platforms, along with student communities. The purposive and snowball sampling methods were combined for broader reach. Snowball sampling was particularly effective in reaching younger, digitally active groups. The sample size was sufficiently large, with demographic considerations to ensure representativeness across all groups. This approach minimized biases associated with generational and demographic factors.

3.2. Measurement Items Development

Questionnaire Structure: The survey used a bifurcated design, where the first section gathered demographic details (e.g., age, gender, education, employment, familiarity with FinTech), and the second focused on measuring behavioral intentions and moderating factors (privacy, technophobia). Measurement items were structured on a five-point Likert scale, ranging from "strongly disagree" (1) to "strongly agree" (5). For the first section, nominal scales were used to capture categorical demographic variables.

Constructs: The study assessed 14 key constructs, with scale items derived from established literature. To ensure the items' relevance to FinTech adoption, the constructs were contextualized within the scope of financial technologies. The scale items were also pretested for clarity and validity before being finalized, ensuring the questionnaire was reliable for collecting meaningful data.

3.3 Respondents Demographic Details

- **Demographic Profile**: Among the 469 respondents, 55.2% were male, and 44.8% were female. The age distribution revealed that 32.6% were aged 25-30 years, suggesting a higher likelihood of FinTech adoption among younger generations. In terms of education, 45.9% held at least a bachelor's degree, reflecting the generally high level of education among the sample. The diversity in income was also noted, with 22.5% of respondents earning between 5,000 and 9,000 INR per month. Table 1 shows the demographic details of the respondents.

- **Technology Usage Patterns**: A significant 79% of respondents used payment technologies (e.g., mobile wallets, UPI, contactless payments), indicating their dominant role in everyday transactions. Additionally, 45.9% engaged with investment technologies (e.g., mutual fund platforms), 19.2% used lending technologies (e.g., peer-to-peer lending), and 10% utilized AI-powered FinTech tools (e.g., chatbots). These findings highlight the varying degrees of familiarity and engagement with different types of FinTech services across generations.

3.3 Statistical Methods

The analysis was conducted using Partial Least Squares Structural Equation Modelling (PLS-SEM), which is particularly suitable for this research due to its flexibility in handling small sample sizes, complex models, and non-normal data distributions. This method was chosen because it can assess both the measurement model (evaluating construct reliability and validity) and the structural model (examining hypothesized relationships) simultaneously. The ability to evaluate higher-order constructs like financial well-being with PLS-SEM further made it a good fit for this study. PLS also enables generating robust predictions with fewer assumptions about the data, making it ideal for a study of this nature (Joseph F. Hair et al., 2019). This technique was selected over others due to its effectiveness in producing accurate results for complex constructs in social science research.

4.1 Common Method Bias

To minimize common method bias (CMB), we applied both procedural and statistical techniques. Procedurally, we ensured respondent anonymity to reduce socially desirable responses (Podsakoff et al., 2003) and clarified scale items using simple, specific language to prevent ambiguity. Additionally, we separated scale items to avoid constructing links that could introduce biases (Parkhe, 1993). To counter acquiescence and disacquiescence biases, we included both positively and negatively framed items (Podsakoff et al., 2012). Respondents who demonstrated straight-lining behavior were excluded, as recommended by Podsakoff et al. (2003) and MacKenzie & Podsakoff, 2012, Furthermore, participants were selected from individuals with prior experience using financial technologies for at least six months.

Statistically, we used the partial correlation procedure Lindell & Whitney, 2001 assess potential method bias. The Harman Single Factor test was employed to check for CMB (Fuller et al., 2016), with results showing no significant bias, as the first factor explained less than 50% of the variance. A marker variable approach further confirmed that CMB did not substantially affect the results, as indicated by a low correlation between the marker variable and other constructs. Additionally, Variance Inflation Factor (VIF) values were below 3.3, ruling out multicollinearity and further confirming minimal bias. These findings suggest that CMB does not significantly impact the validity of the results.

4.2 Measurement Model Analysis

Partial Least Squares Structural Equation Modelling (PLS-SEM) was used to analyze the factors influencing the intention to use financial technologies. This method is suitable for estimating relationships among multiple variables and follows established guidelines for interpreting SEM results (Joseph F. Hair et al., 2019) The first step in analyzing the measurement model is evaluating the reliability and validity of the constructs, including both reflective and formative components (Sarstedt et al., 2019).Given that the financial well-being construct is a reflective-formative higher-order construct, its reliability and validity were assessed before hypothesis testing.

4.2.1 Reliability and Validity

Evaluating the measurement model's reliability and validity is essential in PLS-SEM (Hair et al., 2011). Table 2 , 3 and 4 show the reliability and validity of all the constructs. Four key stages were followed:

1. **Indicator Reliability**: This was assessed by examining factor loadings, with a threshold of 0.70, as recommended by (Hair et al., 2020).All loadings exceeded 0.70, confirming indicator reliability.
2. **Internal Consistency Reliability**: We evaluated this through Composite Reliability (CR), where values above 0.70 indicate acceptable reliability (Hair et al., 2017). All constructs met this criterion, supporting their reliability.
3. **Convergent Validity**: Assessed using the Average Variance Extracted (AVE), with values above 0.50 considered satisfactory(Fornell and Larcker, 2016).All constructs had AVE values greater than 0.50, confirming convergent validity.
4. **Discriminant Validity**: This was tested using the Heterotrait-Monotrait (HTMT) ratio, the Fornell-Larcker criterion, and cross-loadings(Henseler et al., 2015). The HTMT ratio was below the recommended threshold of 0.85, and the square root of the AVE for each construct exceeded the correlations with other constructs, confirming discriminant validity.

4.2.2 Reliability of Higher-Order Construct

The financial well-being construct is a higher-order reflective-formative construct, consisting of lower-order reflective constructs, namely expected future financial security and current money management stress. We evaluated the reliability of both lower-order and higher-order constructs. For lower-order reflective constructs, we assessed internal consistency (via Cronbach's alpha, composite reliability, and ρA), convergent validity (indicator reliability and AVE), and discriminant validity. For the higher-order formative construct, we applied redundancy analysis, which showed path coefficients greater than 0.7, confirming convergent validity. The Variance Inflation Factor (VIF) for the indicators was below 3, indicating no multicollinearity issues. Bootstrapping analysis with 5,000 subsamples demonstrated that the relationships between the formative indicators and their lower-order constructs were statistically significant, confirming the validity of the higher-order construct. Table 5 shows the outer weights of higher order constructs and Table 6 shows the VIF values of higher order constructs.

4.2.3 Validity of Formative Constructs

For formative constructs like financial well-being, the evaluation process includes examining convergent validity, indicator collinearity, the significance of indicators, and their respective weights (Hair et al., 2017). Our redundancy analysis confirmed convergent validity, as path coefficients between the higher-order construct and its single-item measure were greater than 0.7. Multicollinearity was not a concern, with all VIF values below the threshold of 3. Further bootstrapping analysis indicated the statistical significance of all formative indicators, validating the higher-order construct.

4.5 Structural Model Analysis

After confirming the measurement model's reliability and validity, the next step in the PLS analysis was to assess the structural model and test the hypothesized relationships. Initially, the relationships were examined in the main model without the moderator, followed by an interaction model to analyze the moderation effect (Becker et al., 2018; Hair et al., 2010). Path coefficients were tested using PLS bootstrapping with 5,000 re-samples in SmartPLS.

The assessment steps include evaluating Path Coefficients, R^2, Effect Size (f^2), Predictive Relevance (Q^2), and Variance Inflation Factor (VIF). All VIF values were below the 3.3 threshold, indicating no significant multicollinearity (Kock, 2015). The outcomes, including path coefficients and significance levels, are presented in Table 9 and Figure 2.

The R^2 values revealed varying predictive strengths across constructs. For instance, Behavioral Intention (BI) had the highest R^2 value (0.825), while Financial Inclusion (FI) and Hedonic Motivation (HM) showed moderate predictive relevance (0.645 and 0.525, respectively). Task Technology Fit (TTF) and Financial Well-being (FWB) had strong predictive relevance with R^2 values of 0.857 and 0.861. Table 7 shows the R square values of all the dependent constructs. The Q^2 values were also assessed using the blindfolding method, showing strong predictive relevance for BI (0.633) and TTF (0.725). A Q-square value greater than zero indicates that the model's predictive accuracy for an endogenous construct is sufficient (Ringle et al., 2020; Sarstedt et al., 2014, 2017). Effort expectancy (EE) closely followed with a Q^2predict of 0.627, Financial inclusion (FI) displayed a lower predictive capability, with a Q^2predict of 0.409, suggesting that this construct may be more challenging to predict accurately. Financial self-efficacy (FSE) demonstrated strong predictive relevance with a Q^2predict of 0.656. Hedonic motivation (HM) had a Q^2predict of 0. 518.The financial well-being (FWB) showed a Q^2predict of 0.584, IT Mindfulness (MD) yielded a Q^2predict of 0.428, indicating relatively lower predictive accuracy. Perceived ease (PE) demonstrated a Q^2predict of 0.600, Technological self-efficacy (TSE) had a Q^2predict of 0.589. Task technology fit (TTF) exhibited the highest predictive performance among the constructs, with a Q^2predict of 0. 725.Lastly, Usage (USB) also showed strong predictive capability, with a Q^2predict of 0.703.

Collectively, these results underscore the varying levels of predictive accuracy across the constructs, offering valuable insights for further analysis and interpretation

The model's fit was assessed using the SRMR, which yielded a value of 0.04, indicating a strong fit (Henseler et al., 2015). Effect sizes (f^2) revealed that AI significantly influences several constructs, including Effort Expectancy (EE) and Financial Self-Efficacy (FSE), with AI's impact on these constructs showing the strongest effects.
In PLS-SEM analysis, the effect size (f-square) indicates the magnitude of change in an endogenous variable due to variations in an exogenous variable. (Hair et al., 2014, 2019, 2020; Sarstedt et al., 2017). The analysis of the f-square values reveals the strength of the associations between different constructs in the study (see Table 11). Artificial Intelligence (AI) significantly influences several constructs, with the strongest effect on effort expectancy (EE) at 0.751 and financial self-efficacy (FSE) at 0.742, indicating that enhancements in AI can lead to considerable improvements in these areas. AI also has a notable impact on IT mindfulness (HM) with an f-square of 0.520 and on IT mindfulness (MD) at 0.761, emphasizing its pivotal role. Additionally, AI positively affects performance expectancy (PE) with an f-square of 0.590 and technological self-efficacy (TSE) with 0.486. Conversely, behavioral intention (BI) shows a modest effect on user satisfaction behavior (USB) at 0.215, while effort expectancy (EE) influences BI at 0.183. Financial inclusion (FI) has a medium effect on financial wellbeing related to financial well-being with an f-square of 0.275. Among the other relationships, financial self-efficacy (FSE) has a strong influence on task technology fit (TTF) at 0.573, while mindfulness (MD) impacts various constructs, with the strongest influence on TSE at 0.217. The relationship between performance expectancy (PE) and BI is positive at 0.091. The usage of financial technologies (USB) construct exhibits substantial effects on financial inclusion (FI) and life values related to financial well-being, with f-squares of 1.413 and 2.825, respectively. Lastly, the interaction effects between privacy risk (PR) and other constructs on behavioral intention (BI) are minimal, with f-squares ranging from 0.006 to 0.018, while the interaction between technophobia (TB) and BI on USB is slightly more significant at 0.159. Overall, these findings underscore the varying degrees of influence among the constructs, providing valuable insights for understanding the underlying dynamics within the model.

Hypotheses were validated through PLS-SEM, with significant path coefficients supporting the proposed relationships. AI had substantial effects on Performance Expectancy ($\beta = 0.615$), Effort Expectancy ($\beta = 0.686$) and IT Mindfulness ($\beta = 0.657$), confirming H1a, H1b, and H1c. IT Mindfulness also showed significant effects on Performance Expectancy ($\beta = 0.245$) and Effort Expectancy ($\beta = 0.164$), supporting H2a and H2b.

The assessment also found strong influences of Financial Self-Efficacy (FSE) and Technological Self-Efficacy (TSE) on Task Technology Fit (TTF), supporting H3A and H3B. Furthermore, significant relationships were found between Performance

Expectancy (PE), Effort Expectancy (EE), Hedonic Motivation (HM), and Behavioral Intention (BI), supporting H4A, H4B, and H4C.

The structural model assessment indicated a significant relationship between **TTF (Task Technology Fit)** and **BI (Behavioral Intention).** The path coefficient for TTF to BI was ($\beta = 0.165$, $p < 0.05$), supporting Hypothesis H5. The relationship between Behavioral Intention (BI) and Usage Behavior (USB) was confirmed ($\beta = 0.311$), supporting H6, while increased usage was linked to higher Financial Well-being (FWB) and Financial Inclusion (FI), supporting H7A and H8A.

4.6 Moderation Results

Moderation analysis revealed that Technophobia (TB) negatively moderates the relationship between Behavioral Intention (BI) and Usage Behavior (USB) ($\beta = -0.289$, $p < 0.05$), suggesting that technophobia reduces the impact of behavioral intention on usage. Privacy Risk (PR) also moderated the relationship between Performance Expectancy (PE) and Behavioral Intention (BI) with a significant negative effect ($\beta = -0.148$, $p < 0.05$).

5. Discussion

This research investigated consumers' intentions.to use financial technologies and the effect of AI Intelligence as well as IT mindfulness is studied. Furthermore, the effect of the adoption of financial technologies on users' financial well-being was also explored. The study also took into consideration the moderating impact of privacy risk and Technophobia on the various antecedents and behaviors of using fintech. To better understand consumers' behavior and intention to use financial technologies, the research further delves into the influence of the Artificial intelligence of fintech services on Performance expectancy, Effort expectancy, and Hedonic motivation. Further, their effect on behavioral intention to adopt FinTech services. was also studied. Information was gathered from fintech users and tested using the PLS-SEM. The findings demonstrated substantial validation for all but one hypothesis, suggesting that the proposed research model effectively accounts for consumers' adoption of FinTech services. The results highlight the pivotal role of factors like Artificial Intelligence in shaping FinTech services. Moreover, the study emphasizes how the efficacy of AI intelligence Moreover, the study emphasizes how the efficacy of AI intelligence can transform a behavior intention to use fintech. The subsequent section provides an analysis of the explanations for the findings.

Our study combines existing empirical evidence to offer a thorough understanding of the key factors that drive the intention to use FinTech services and their outcomes. This study sought to enhance our comprehension of the role of artificial intelligence along with the mindfulness of the intention to use fintech services through their impact on UTUAT variables.

The findings of this research expand and profoundly deepen our existing understanding of the factors that drive consumers to embrace and adopt FinTech, with a particular focus on the roles of artificial intelligence and mindfulness in the

following ways. We drew on UTAUT, Task technology fit artificial intelligence and IT mindfulness along with efficacy to develop the model to understand the factors that influence consumer behavioral intentions towards using fintech as well as the role of AI that affects fintech adoption. We examined a total of 26 (including sub hypothesis) including sub hypothesis that can be categorized into three distinct groups: factors related with Technology adoption, factors that act as moderators, and factors that act as the outcomes.

Our findings enhance the understanding of how AI can influence consumers' reactions. in fintech settings. Based on the path coefficient analyses, (see Table 9), the research hypotheses related to the impact of artificial intelligence on performance expectancy, effort expectancy, and hedonic motivation were found to be significant. The most prominent causal relationship was observed between AI and performance expectancy (H1a). This indicates that FinTech users who experience AI-driven features that enhance efficiency and ease of use tend to have higher performance expectations. AI's capability to provide personalized, accurate, and timely assistance aligns with users' desires for convenience and enjoyment, thereby enhancing hedonic motivation. These findings align with prior research (Smith et al., 2019; Zhang and Lin, 2021) that emphasize AI's role in elevating user expectations and satisfaction in technology adoption contexts. Moreover, the research hypotheses concerning the effect of artificial intelligence on IT mindfulness were also supported and found to be significant. The most significant causal relationship was observed between AI and mindfulness (H1d).

This suggests that users exposed to AI-enhanced FinTech services, which offer personalized and context-aware assistance, are more likely to engage in mindful interactions with the technology. AI-driven recommendations and tailored feedback foster a sense of awareness and presence, allowing users to make more informed and deliberate financial decisions. These results align with previous findings Wang & Uysal (2024) and Oeldorf-Hirsch & Chen, 2022 which highlight the role of AI in promoting IT mindfulness by enhancing users' focus and cognitive engagement during technology use. The analysis of path coefficients also reveals that the impact of artificial intelligence on technological self-efficacy in FinTech services is significant, supporting the related hypotheses. The most pronounced causal link was observed between AI and technological self-efficacy. This relationship indicates that AI-powered features in FinTech services, such as intuitive interfaces, automated guidance, and personalized support, empower users to feel more competent and confident in their ability to navigate and utilize the technology effectively. Enhanced AI-driven experiences simplify complex tasks and reduce perceived effort, thus boosting users' technological self-efficacy. These findings align with the results presented Montag et al.(2023) and Nah & McNealy(2024)which emphasize AI's role in fostering users' confidence and proficiency in engaging with digital financial platforms.

Consistent with recent research, the data show that performance expectancy, effort expectancy, and hedonic motivation are significant factors influencing consumers'

behavioral intention to use FinTech services. Performance expectancy, which reflects the perceived benefits of using FinTech services, positively impacts consumers' intention to adopt these services, as users believe that FinTech solutions can enhance their financial management capabilities (Bajunaied et al., 2023; Chan et al., 2022; Zhou et al., 2023). Effort expectancy, or the perceived ease of use of FinTech services, also plays a crucial role, having a positive impact on behavioral intention, since users are more inclined to engage with technologies that are intuitive and require minimal effort ((Al-Okaily et al., 2020; Xie et al., 2021). Additionally, hedonic motivation, which captures the enjoyment and pleasure derived from using FinTech services, significantly affects behavioral intention. This aligns with recent (Bommer et al., 2023; Ryu, 2018), suggesting that when users find FinTech services not only useful and easy to use but also enjoyable, their likelihood of adoption increases.

The results of the impact of IT mindfulness on performance expectancy, effort expectancy, technological self-efficacy, and financial self-efficacy were also significant, supporting the corresponding hypotheses. IT mindfulness positively influenced performance expectancy, suggesting that users who are more mindful in their interactions with technology perceive FinTech services as more beneficial in achieving their financial objectives. Likewise, IT mindfulness positively impacted effort expectancy (H2), indicating that mindful users find FinTech services easier to use, as they are more attentive and deliberate when engaging with technology. Furthermore, IT mindfulness significantly enhanced technological self-efficacy and financial self-efficacy, implying that users with higher levels of IT mindfulness feel more confident in their ability to effectively use technology and manage their finances. However, the hypothesis related to the impact of IT mindfulness on hedonic motivation (H5) was not supported. This indicates that while IT mindfulness aids users in recognizing the usefulness and ease of FinTech services, it does not necessarily increase the enjoyment or pleasure derived from using these services. This result diverges from previous studies ((Flavian et al., 2020; Wu et al., 2022) which suggested a positive connection between IT mindfulness and hedonic outcomes, underscoring the complex and varied influence of IT mindfulness in the context of FinTech service adoption.

An interesting finding was that the impacts of financial self-efficacy and technological self-efficacy on Task Technology Fit (TTF) were significant, supporting the respective hypotheses. Financial self-efficacy positively influenced TTF (H3a), indicating that users who are confident in their financial management skills perceive a better alignment between the tasks they need to perform and the capabilities offered by FinTech services. Similarly, technological self-efficacy was found to have a strong positive effect on TTF (H3b), suggesting that users who feel proficient in using technology are more likely to perceive FinTech services as well-suited to their needs, enhancing their overall task performance(Strong et al., 2006).

Additionally, Task Technology Fit was shown to have a significant positive impact on behavioral intention to use FinTech services (H5). This finding implies that when users perceive a good fit between the tasks they need to accomplish and the

technology available, they are more likely to develop a strong intention to use FinTech services. This aligns with findings from recent studies (Ojiaku et al., 2024), which emphasize that a high degree of task-technology alignment can significantly boost users' intentions to engage with technology. These results highlight the critical role of both financial and technological self-efficacy in shaping users' perceptions of TTF and, subsequently, their behavioral intentions toward FinTech adoption.

The results also revealed that behavioral intention exerts a significant positive effect on the actual use of FinTech services. (H7), strongly supporting the hypothesis. This relationship implies that when users are strongly inclined to adopt FinTech services, motivated by factors like perceived usefulness, ease of use, and enjoyment, they are more likely to translate these intentions into actual usage behavior. The findings align with the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), both of which assert that behavioral intention is a key predictor of technology adoption(Bajunaied et al., 2023; Singh et al., 2020)). Recent studies further confirm that the strength of behavioral intention significantly determines the frequency and extent of FinTech service usage ((Belanche et al., 2022; Patil et al., 2020; Ramayanti et al., 2024) highlighting that users who exhibit higher behavioral intention are more likely to engage consistently with FinTech platforms. This underscores the importance of enhancing behavioral intention to boost the adoption and usage rates of FinTech services among users.

The usage of FinTech services has been shown to significantly enhance financial well-being and promote financial inclusion among users. By providing accessible, convenient, and personalized financial tools, FinTech platforms empower users to make informed financial decisions, thereby improving their overall financial health (Aggarwal et al., 2023; Dzogbenuku et al., 2022; J. Kumar et al., 2023) Additionally, FinTech services reduce barriers to financial access, facilitating inclusion by reaching underserved populations and offering tailored financial solutions (Kanungo & Gupta, 2021; Suryono et al., 2020). While previous research has explored aspects of FinTech's impact, this study contributes by empirically examining the dual effects of FinTech adoption on financial well-being and financial inclusion, thus establishing a link between technology (Brüggen et al., 2017; Lone & Bhat, 2024).

Apart from that, results also suggest that technophobia negatively moderates the relationship between behavioral intention and the actual usage of FinTech services, potentially hindering the adoption process. Specifically, individuals with high levels of technophobia may experience anxiety and discomfort when interacting with FinTech platforms, which weakens their behavioral intention to use these services and reduces actual usage (H9 Supporting prior findings, his result indicates that when users harbour fears or negative attitudes toward technology, even strong behavioral intentions are less likely to translate into actual usage ((Hussain et al., 2024; Palash et al., 2022);. In essence, technophobia acts as a significant barrier, dampening the conversion of intention into action, and consequently impacting the overall adoption of FinTech services. Thus, addressing technophobia is crucial in

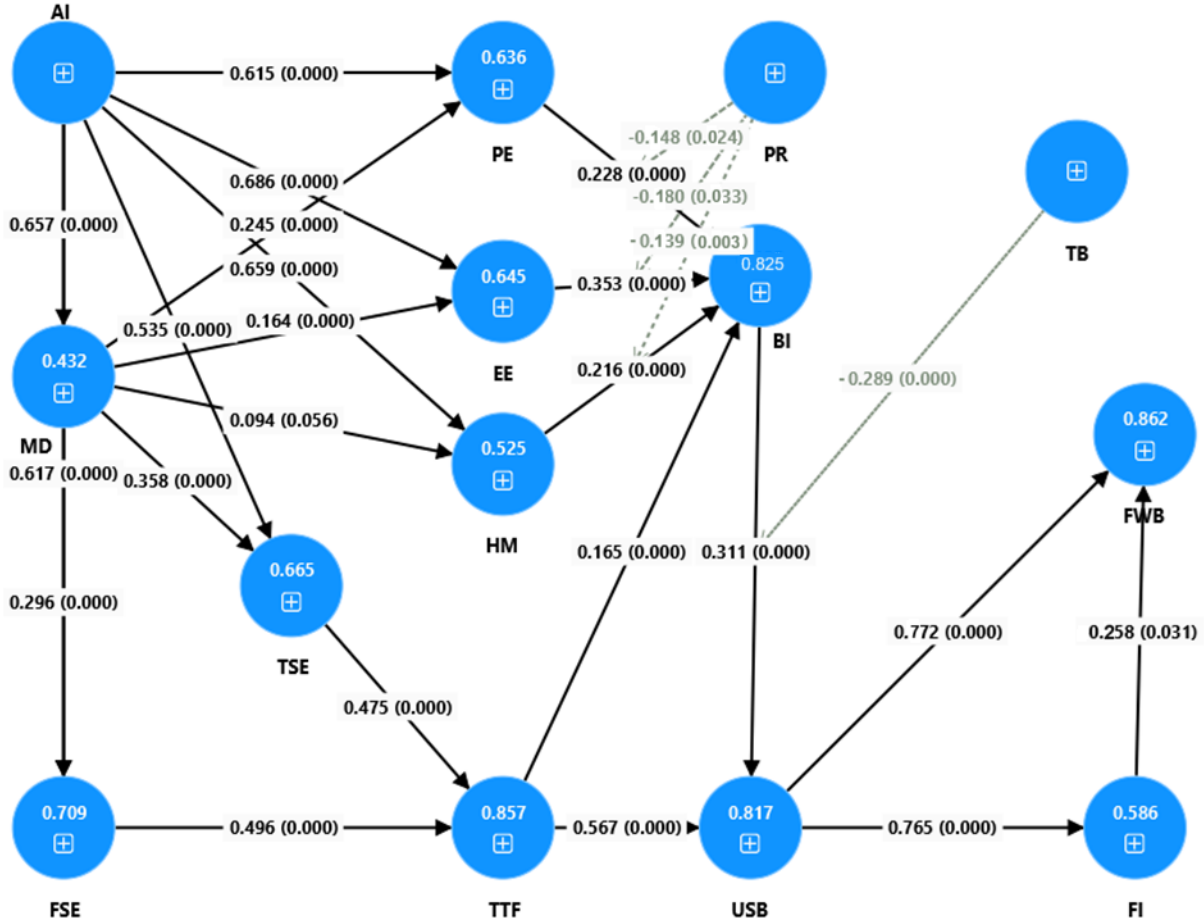
mitigating its adverse effects on user engagement and fostering the widespread adoption of FinTech solutions.

This finding highlights that privacy risk significantly moderates the effects of performance expectancy, effort expectancy, and hedonic motivation on behavioral intention to use FinTech services. When privacy concerns are high, the positive impacts of these antecedents on behavioral intention are substantially weakened. Specifically, users who perceive high privacy risks are less likely to act on their belief in the benefits (performance expectancy) of FinTech services, as their concerns about data security overshadow perceived advantages (H1). Similarly the impact of effort expectancy on behavioral intention weakens. under high privacy risk, as users may perceive the ease of use as inadequate compensation for potential data vulnerabilities (H2). Moreover, privacy risk also negatively moderates the relationship between hedonic motivation and behavioral intention (H3). Even when users find FinTech services enjoyable, heightened privacy concerns can dampen their overall intention to adopt these services. These findings align with prior research (Choi et al., 2023; Kim et al., 2023; Lee and Park, 2022), which consistently demonstrate that privacy concerns act as a significant barrier, reducing the effectiveness of otherwise positive motivators in driving technology adoption. Addressing privacy risks is therefore crucial in enhancing the impact of performance expectancy, effort expectancy, and hedonic motivation on behavioral intention to use FinTech services (Xu et al., 2023; Li and Liu, 2022; Zhang et al., 2023).

The study examined the impact of **Artificial Intelligence (AI) on the Unified Theory of Acceptance and Use of Technology (UTAUT)** constructs, including performance expectancy, effort expectancy, and hedonic motivation, as well as its effects on mindfulness, financial self-efficacy, and technological self-efficacy. All hypotheses were supported except for the influence of mindfulness on hedonic motivation. This indicates that fintech users who utilize AI in financial services perceive AI-driven, customer-centric solutions—such as personalized financial advice and AI assistants—as facilitating continuous and streamlined interactions, ultimately enhancing their performance expectancy from fintech services. Additionally, users recognize that AI-driven personalization, natural language processing through virtual agents and chatbots, and automated payment processing contribute to unique banking experiences. AI acts as an enabler, systematizing banking processes, tracking essential transactions, and improving the overall quality of banking experiences. Given that AI-dominated services are tailored to individual needs, they also help mitigate service bottlenecks. User-friendly AI interfaces, which banking and financial experts trust, offer timely and relevant support, allowing users to perform transactions efficiently and avoiding unnecessary delays. These interfaces, designed with advanced technologies, analyze users' financial patterns and work on behalf of banks to enhance user experience. Managers advocate for an AI-centric banking ecosystem due to the intelligent dynamics these interfaces provide. The implementation of AI-enabled services has increased user comfort and reduced the necessity for frequent bank visits, aided by AI service assistants, chatbots, and navigational tools. Together, these findings underscore the importance

of exploring how AI empowers individuals to make informed health-related decisions, particularly in the context of adherence to wearable self-care technologies.

Fig 2: Structural Model showing the beta values and R^2 Values



Source: Authors own Source

6. CONCLUSION

6.1 Theoretical implication

Firstly, this study significantly contributes to the existing literature by extending the Unified Theory of Acceptance and Use of Technology (UTAUT2) in conjunction with Task Technology Fit (TTF)and by Integrating the model with technological constructs like AI intelligence and psychological constructs like IT mindfulness and Technological self-efficacy and financial self-efficacy to enhance specifically focusing on financial well-being and financial inclusion as key outcomes. This extension provides a more comprehensive framework for understanding the broader socio-economic impacts of FinTech adoption(Abis et al., 2024). In particular, the findings demonstrate that constructs such as performance expectancy, effort expectancy, and Hedonic motivation contribute significantly to explaining the variance in behavioral intention, which in turn influences actual usage and subsequent financial well-being. Existing studies have not intended to explain such behavior (Li et al., 2018) and the requirement to combine both antecedents and outcome variables has been largely

neglected in the FinTech adoption literature. (Agogo & Hess, 2018).To address this gap, our model provides a valuable approach that considers antecedents, outcomes. As well as moderators when studying the adoption of financial technologies. Furthermore, the study identifies financial inclusion as a direct outcome of FinTech usage, highlighting that increased accessibility to financial services through technology can enhance financial resilience among users (Demirgüç-Kunt et al., 2018 As a result, this research stands to make a profound contribution to the formulation of a more sophisticated theoretical framework for comprehending fintech adoption and its far-reaching implications for the development of business strategies and informed decision-making.

Secondly, by integrating AI intelligence into the UTAUT2 model, enhancing its explanatory power in the context of FinTech adoption. The inclusion of AI intelligence addresses the growing role of AI-driven features such as personalization, predictive analytics, and automated decision-making in influencing user expectations and perceptions of FinTech services ((Rrustemi & Tuchschmid, 2020)). The results indicate that AI intelligence positively influences key constructs like performance expectancy and effort expectancy, which together explain a substantial portion of the variance in behavioral intention towards FinTech adoption. This finding underscores the importance of advanced AI capabilities in enhancing the perceived usefulness and ease of use of FinTech applications, thereby driving user acceptance and continued usage (Dwivedi et al., 2021). Moreover, this study expands the current understanding by demonstrating that AI not only improves functional aspects of technology adoption but also enhances user trust and satisfaction through personalized and efficient service delivery (Huang & Rust, 2018). By integrating AI intelligence into UTAUT2, this research provides a modernized framework that captures the dynamic and evolving nature of FinTech services, offering valuable insights into how advanced technological features impact user behavior (Dwivedi et al., 2021; Huang & Rust, 2018).

Third, this study expands the understanding of individual characteristics by incorporating IT mindfulness as a key factor in the FinTech adoption process. While much of the existing research focuses on cognitive aspects such as perceived usefulness and ease of use, there is limited exploration of how psychological traits like IT mindfulness affect technology adoption (Brown & Ryan, 2003; Thong et al., 2016). Our study introduces and empirically validates mindfulness as a predictor of technological and financial self-efficacy, which in turn influences behavioral intention towards using FinTech services. This addition provides valuable insights into the affective dimension of technology interaction, suggesting that IT mindfulness can significantly enhance user engagement and adaptability in digital finance contexts. By integrating IT mindfulness into the UTAUT2 model, we contribute new constructs that enrich the IT adoption literature and deepen our understanding of the factors driving behavioral intention, particularly in the realm of FinTech (Brown & Ryan, 2003; Bandura, 1997). In terms of originality, to the best of our knowledge, this is among the pioneering studies that empirically establish the role of IT mindfulness in the adoption of financial technology.

Fourthly, we make a significant contribution to the burgeoning literature on using Fintech for financial well-being. No studies have taken into account the effect of financial technology adoption on the financial well-being of the user. Although few conceptual studies have highlighted the importance of variables like financial literacy (Lone & Bhat, 2024), financial capability (Xiao et al., 2024), and financial attitude (Bhatia and Singh, 2024) in financial well-being, there is a gap in the literature regarding the role of financial technology as a direct determinant of financial well-being, necessitating further exploration of how FinTech adoption can influence financial outcomes for individuals. They study provides insight into how the individual adoption of financial technologies Impacts financial well-being from the standpoint of an individual.

Furthermore, this study has proposed financial well-being as an outcome of adoption and this linkage offers a novel perspective on the broader socio-economic impacts of FinTech services, aligning technology adoption theories with public policy goals of enhancing financial resilience and access (Demirgüç-Kunt et al., 2018).

This study introduces technophobia as a moderating factor between behavioral intention and actual usage of FinTech services, which adds a new layer of understanding to the technology adoption literature. While much of the existing research focuses on cognitive and functional aspects of technology acceptance, the inclusion of technophobia emphasizes the emotional and psychological dimensions that can impede technology use (Sinkovics et al., 2007). This addition recognizes that not all users approach FinTech services with the same level of comfort and openness and that negative emotions like fear can significantly disrupt the pathway from intention to actual usage. From a practical perspective, understanding the role of technophobia can guide the development of more inclusive FinTech solutions that cater to tech-averse populations. This might include features designed to simplify user interfaces, offer step-by-step guidance, or incorporate elements that reduce anxiety, thereby making FinTech services more accessible to a broader range of users.

6.2 Practical /Managerial Implication

The value of this study transcends its theoretical framework, offering profound practical implications through a series of strategic recommendations intended to guide marketers and designers of financial technologies. The practical implications of this study provide valuable guidance for FinTech providers, policymakers, and practitioners aiming to enhance the adoption and impact of FinTech services. First, by highlighting the importance of financial well-being and inclusion as outcomes, the study suggests that FinTech solutions should be designed with features that promote accessibility and financial education, thereby supporting broader socio-economic goals (Demirgüç-Kunt et al., 2018). For FinTech providers, this means prioritizing inclusivity in product design, such as offering simplified interfaces and targeted support for underbanked populations.

The integration of AI intelligence into the adoption model underscores the need for FinTech companies to leverage advanced AI-driven features like personalization and predictive analytics to improve user experience and engagement(Dwivedi et al., 2021) However, the study also emphasizes the importance of balancing these innovations with robust privacy measures, as privacy risk is shown to significantly influence user trust and adoption decisions (Goel et al., 2022). Implementing clear and transparent data privacy policies, along with strong security protocols, can help mitigate user concerns and build confidence in FinTech services.

Furthermore, the inclusion of psychological factors such as IT Mindfulness and technophobia highlights the need for FinTech providers to consider user readiness and comfort levels. Offering educational resources, user training, and responsive customer support can help address technophobia and enhance users' self-efficacy, making FinTech services more accessible to a diverse range of users (Garg et al., 2023). Overall, these insights encourage a holistic approach to FinTech service design that considers not only technological advancements but also user perceptions, trust, and psychological readiness, ultimately fostering a more inclusive and user-friendly digital financial environment.

6.3 Limitations and Recommendations for future research

While this study provides both theoretical and practical contributions to the field of financial technologies, as outlined above, several limitations warrant consideration and could be addressed in future research. The current model is based on two frameworks, UTAUT2 and TTF, along with additional technological constructs**.** Future research may combine theories such as the **Diffusion of Innovations (DOI)** to understand the adoption process over time, **Self-Determination Theory (SDT)** to assess the impact of intrinsic and extrinsic motivations, and **Innovation Resistance Theory (IRT)** to identify potential barriers to technology acceptance.
Secondly, Our study incorporated Artificial intelligence as an important technological variable, we also suggest the adoption of alternative technological variables, such as environmental sustainability of technology, and data portability as these constructs have seldom been utilized in the existing literature and could offer valuable additional insights. Additionally, it is essential to address the perceived negative aspects and potential risks associated with the use of AI. These concerns represent critical issues that must be thoroughly examined and appropriately mitigated.

Thirdly, our study includes two new psychological constructs IT mindfulness and Technological self-efficacy and financial self-efficacy that are relevant to using financial technology. Our findings affirm that the incorporation of this element offers a more nuanced understanding and a more precise prediction of users' attitudes and behavioral intentions. Thus, future work could also identify other psychological variables like perceived cognitive load, digital minimalism, and technological curiosity and investigate other pertinent personal factors that are critical to the research context.

While the study includes key moderators like privacy risk and technophobia, there may be other relevant factors influencing FinTech adoption that were not considered. Future research could also examine the impact of such as digital detachment, tech -Nostalgia, cognitive flexibility, algorithmic trust, and digital responsibility, which may offer additional insights into user behavior and the nuanced ways in which individuals engage with financial technologies.

The data for the present study were gathered through purposive sampling of individuals who are actual users of financial technologies. Consequently, there may be concerns regarding the generalizability of the findings to other customer segments who have not engaged with financial technologies. Future research could aim to utilize a more representative sample and consider stratifying the sample by region to account for the substantial cultural variations across the country's diverse states. While, we employed PLS-SEM to examine the hypothesized relationships by evaluating the independent effects of each predictor on the outcomes, we acknowledge the potential for intricate and asymmetrical interdependencies among the variables. Future research should explore multigroup analyses across different countries to identify variations in FinTech usage between advanced and less advanced nations. Additionally, The FinTech industry is rapidly evolving due to constant changes in technologies, regulations, and market dynamics, which may cause the study's findings to become outdated as innovations and shifts in user preferences occur. Future research should incorporate qualitative methods and multimethod approaches to capture a broader and more nuanced understanding of FinTech adoption, ensuring findings remain relevant in the face of industry changes.

Table 1: Demographic Details of the participants

Demographic Factors	**Male**	**Female**	**Total**	**Percentage (%)**
Total Participants	259	210	469	100.0
Age				
18–24	88	64	152	32.4
25–30	121	89	210	44.8
31–40	94	64	158	33.7
41–50	48	34	82	17.5
51–60	34	16	50	10.7
60+	4	34	38	8.1
Total Age	469	469	469	100.0
Monthly Income				
Less than 5,000	96	45	141	30.1
5,001–10,000	95	60	155	33.0
10,001–15,000	124	65	189	40.3
15,001–20,000	78	35	113	24.1
More than 20,000	34	5	39	8.3
Total Monthly Income	469	469	469	100.0
Education Level				
High School	24	20	44	9.4
Diploma	67	122	189	40.3

Bachelor	98	69	167	35.6
Master	38	31	69	14.7
PhD	0	0	0	0.0
Total Education Level	469	469	469	100.0
Financial technologies Experience				
Less than one year	68	32	100	21.3
1–2 years	135	95	230	49.0
2–3 years	154	85	239	51.0
More than 3 years	112	22	134	28.6
	469	469	469	100.0
Types of financial technologies usage				
Financial Technology Types	Male Users	Female Users	Total Users	Percentage
Payment Technologies	200	170	370	79%
Lending Technologies	55	35	90	19.2%
Investment Technologies	120	95	215	45.9%
AI-Powered Fintech Technologies	24	23	47	10%

Source(s): Authors' own creation
Number of participants (N = 469)

Table 2: Constructs Reliability and Validity

Constructs	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AI	0.885	0.899	0.929	0.804
BI	0.892	0.895	0.933	0.823
EE	0.890	0.897	0.924	0.751
FI	0.847	0.906	0.883	0.601
FSE	0.902	0.966	0.973	0.878
HM	0.866	0.877	0.918	0.788
IT MD	0.856	0.876	0.895	0.631
PE	0.890	0.908	0.930	0.770
PR	0.804	0.960	0.928	0.720
TB	0.895	0.985	0.977	0.784
TSE	0.885	0.901	0.916	0.687
TTF	0.834	0.939	0.946	0.717
USB	0.884	0.892	0.928	0.812

Source(s): Authors own creation

Table 3: Discriminant validity – heterotrait–monotrait ratio (HTMT)

CONSTRUCTS	AI	BI	EE	FI	FSE	HM	IT MD	PE	PR	TB	TSE	TTF	USB	PR x EF	PR x HM	PR x PE	TB x BI
AI		0.706	0.781	0.630	0.771	0.712	0.427	0.462	0.447	0.207	0.759	0.233	0.608	0.325	0.271	0.361	0.107
BI			0.536	0.528	0.772	0.585	0.680	0.507	0.303	0.134	0.407	0.632	0.779	0.489	0.439	0.528	0.054
EE				0.560	0.619	1.018	0.659	0.706	0.235	0.117	0.493	0.789	0.350	0.388	0.360	0.387	0.153
FI					0.630	0.488	0.756	0.547	0.446	0.290	0.599	0.645	0.402	0.185	0.132	0.154	0.137
FSE						0.828	0.758	0.764	0.324	0.131	0.372	0.722	0.623	0.430	0.363	0.497	0.127
HM							0.578	0.690	0.225	0.102	0.566	0.691	0.753	0.368	0.444	0.349	0.139
IT MD								0.713	0.405	0.335	0.265	0.792	0.609	0.155	0.130	0.191	0.246
PE									0.231	0.108	0.416	0.720	0.696	0.434	0.377	0.575	0.099
PR										0.327	0.292	0.385	0.402	0.327	0.326	0.189	0.060
TB											0.219	0.153	0.195	0.090	0.116	0.073	0.136
TSE												0.460	0.778	0.253	0.136	0.382	0.277
TTF													0.657	0.349	0.285	0.421	0.175
USB														0.248	0.188	0.325	0.302
PR x EF															0.841	0.817	0.023
PR x HM																0.699	0.184
PR x PE																	0.044
TB x BI																	

Source(s): Authors own creation

Table 4: Discriminant validity Fornell and Larcker

	AI	BI	EE	FI	FSE	HM	IT MD	PE	PR	TB	TSE	TTF	USB
AI	0.896												
BI	0.509	0.907											
EE	0.493	0.626	0.866										
FI	0.611	0.532	0.565	0.775									
FSE	0.712	0.507	0.760	0.625	0.937								
HM	0.521	0.469	0.592	0.491	0.763	0.887							
IT MD	0.657	0.518	0.615	0.619	0.402	0.528	0.795						
PE	0.476	0.606	0.468	0.548	0.603	0.591	0.649	0.877					
PR	0.422	0.293	0.235	0.416	0.315	0.211	0.347	0.228	0.849				
TB	0.029	0.018	0.048	0.257	0.132	0.016	0.276	0.045	0.292	0.885			
TSE	0.670	0.708	0.606	0.584	0.717	0.671	0.509	0.623	0.215	0.044	0.829		
TTF	0.557	0.461	0.626	0.446	0.782	0.423	0.426	0.526	0.369	0.069	0.688	0.847	
USB	0.412	0.787	0.670	0.365	0.752	0.569	0.604	0.406	0.377	0.189	0.877	0.774	0.901

Source(s): Authors own creation

Table 5: Outer weights of higher order reflective formative construct

Constructs	VIF Values	Outer weights
FWB-> FWB1	2.967	0.239
FWB -> FWB2	2.345	0.781

Source(s): Authors own creation

Table 6: Table showing the variance inflation Factor

Inner VIF values	VIF
AI -> EE	1.753
AI -> FSE	1.753
AI -> HM	1.753
AI -> PE	1.753
AI -> TSE	1.753
BI -> USB	3.280
EE -> BI	2.317
FSE -> TT	3.012
HM -> BI	2.070
PE -> BI	2.249
PR -> BI	1.181
TB -> USB	1.035
TSE -> TT	3.012
TT -> USB	2.605
USB -> FI	1.000
USB -> FWB	1.000
IT MD -> EE	1.753
IT MD -> FSE	1.753
IT MD -> HM	1.753
IT MD -> PE	1.753
IT MD -> TSE	1.753
PR x EE -> BI	2.839
PR x HM -> BI	2.239
PR x PE -> BI	2.597
TB x BI -> USB	1.209

Source(s): Authors own creation

Table 7: Coefficient of Determination

Constructs	**R-square**	**R-square adjusted**
BI	0.825	0.824
EE	0.645	0.644
FI	0.586	0.585
FSE	0.709	0.708
HM	0.525	0.524
FWB	0.862	0.862
IT MD	0.432	0.432
PE	0.636	0.635
TSE	0.665	0.665
TTF	0.857	0.857
USB	0.817	0.816

Source(s): Authors own creation

Table 8: PLS PREDICT SUMMARY ($Q^{2)}$

Constructs	Q^2predict
BI	0.633
EE	0.627
FI	0.409
FSE	0.656
HM	0.518
FWB	0.584
IT MD	0.428
PE	0.600
TSE	0.589
TTF	0.725
USB	0.703

Source(s): Authors own creation

Table 9: Result of hypotheses testing

S.no	Hypothesis	Path Coefficient	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Result
1	H1a	AI -> PE	0.615	0.614	0.057	10.762	0.000	Supported
2	H1b	AI -> EE	0.686	0.686	0.047	14.602	0.000	Supported
3	H1c	AI -> HM	0.659	0.660	0.048	13.781	0.000	Supported
4	H1d	AI -> IT MD	0.657	0.657	0.029	22.806	0.000	Supported
5	H1e	AI -> FSE	0.617	0.616	0.057	10.828	0.000	Supported
6	H1f	AI -> TSE	0.535	0.534	0.059	9.048	0.000	Supported
7	H2a	IT MD -> PE	0.245	0.245	0.052	4.735	0.000	Supported
8	H2b	IT MD -> EE	0.164	0.163	0.046	3.588	0.000	Supported
9	H2c	IT MD -> HM	0.094	0.093	0.049	1.910	0.056	Not Supported
10	H2d	IT MD -> TSE	0.358	0.358	0.057	6.229	0.000	Supported
11	H2e	IT MD -> FSE	0.296	0.297	0.053	5.622	0.000	Supported
12	H3a	FSE -> TTF	0.496	0.497	0.034	14.494	0.000	Supported
13	H3b	TSE -> TTF	0.475	0.474	0.039	12.323	0.000	Supported
14	H4a	PE -> BI	0.228	0.226	0.037	6.113	0.000	Supported
15	H4b	EE -> BI	0.353	0.350	0.053	6.707	0.000	Supported
16	H4c	HM -> BI	0.216	0.222	0.050	4.340	0.000	Supported
17	H5a	TTF -> BI	0.165	0.165	0.033	4.941	0.000	Supported
18	H5 b	TTF -> USB	0.567	0.568	0.057	9.876	0.000	Supported
19	H6	BI -> USB	0.311	0.310	0.060	5.215	0.000	Supported
20	H7	USB -> FWB	0.772	0.973	0.019	51.640	0.000	Supported

21	H8a	USB -> FI	0.765	0.766	0.020	37.482	0.000	Supported
22	H8b	FI -> FWB	0.258	-0.060	0.027	2.187	0.031	Supported
23	H9	TB x BI -> USB	-0.289	0.287	0.043	6.654	0.000	Supported
24	H10 a	PR x EE -> BI	-0.180	-0.084	0.053	1.501	0.033	Supported
25	H10 b	PR x HM -> BI	-0.139	0.042	0.042	0.923	0.003	Supported
26	H10 c	PR x PE -> BI	-0.148	-0.047	0.031	1.538	0.024	Supported

Note(s): ***p < 0.001, **p < 0.01, *p < 0.05, ns: not significant (based on t (10.000), two-tailed test) Source(s): Authors' own creation

Table 10: Model Fit Indices

Model Fit Indices	Saturated model	Estimated model
SRMR	0.111	0.138
d_ULS	27.188	42.275
d_G	n/a	n/a
Chi-square	∞	∞
NFI	n/a	n/a

Table 11: Effect size (F^2)

Constructs	**f-square**
AI -> EE	0.751
AI -> FSE	0.742
AI -> HM	0.520
AI -> MD	0.761
AI -> PE	0.590
AI -> TSE	0.486
BI -> USB	0.215
EE -> BI	0.183
FI -> FWB	0.275
FSE -> TTF	0.573
HM -> BI	0.102
MD -> EE	0.043
MD -> FSE	0.171
MD -> HM	0.011
MD -> PE	0.093
MD -> TSE	0.217
PE -> BI	0.091
PR -> BI	0.008
TB -> USB	0.089
TSE -> TTF	0.524
TTF -> BI	0.076
TTF -> USB	0.373
USB -> FI	1.413
USB -> FWB	2.825

PR x EE -> BI	0.018
PR x HM -> BI	0.006
PR x PE -> BI	0.011
TB x BI -> USB	0.159

Source(s): Authors own creation

Appendix A
Measurement Items Development

S.no.	Constructs	Reference
1.	AI Intelligence	Schepman & Rodway, 2020
2.	IT Mindfulness	Thatcher et al., 2018
3.	Financial self-efficacy	Lown M. Jean, 2011
4.	Technological self-efficacy	Horzum & Çakir, 2009
5.	Task Technology fit	Oliveira & Tam, 2016
6.	Performance expectancy	Venkatesh et al., 2012
7.	Effort expectancy	Venkatesh et al., 2012
8.	Hedonic motivation	Venkatesh et al., 2012
9.	Behaviour intention	Venkatesh et al., 2012
10.	Actual usage	Moon & Kim, 2001
11.	Financial wellbeing	Netemeyer et al, 2018
12.	Financial inclusion	Mindra et al., 2017
13.	Technophobia	Martínez-Córcoles et al., 2017
14.	Privacy risk	Featherman & Pavlou, 2003
15.		

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