Vol. 06, No. 4 (2024) 1439-1454, doi: 10.24874/PES06.04.003

Proceedings on Engineering Sciences

www.pesjournal.net

EXPLORING USER PERSPECTIVES ON THE APPLICATIONS OF ARTIFICIAL INTELLIGENCE IN FINANCIAL TECHNOLOGY

Sadhana Tiwari[1]
Mohammad Asif
Amar Johari
Mohammad Wasiq
Mohd Imran

Received 12.03.2024.
Received in revised form 14.07.2024.
Accepted 18.08.2024.
UDC – 004.8

Keywords:

Structural equation modeling, Perceived Usefulness, Perceived Privacy and Security, Perceived Ease of Use, Satisfaction of Fintech AI, adoption of Fintech AI

A B S T R A C T

This study investigates the factors influencing the adoption of fintech AI among 397 government college students from middle-class families in Haryana, India. Structural equation modeling was employed to study the relationships between the adoption of fintech AI and its predictors, namely Perceived Usefulness, Perceived Privacy and Security, Perceived Ease of Use, and Satisfaction of Fintech AI.

This study utilized a cross-sectional research design. In this study, a non-probability convenience sampling method was utilized. The researchers opted for a sample of 397 government college students, consisting of 200 males and 197 females, hailing from middle-class families in Haryana, India. This sampling approach was selected because of its simplicity and ease of access, as it enabled the researchers to effortlessly connect with participants without resorting to random selection. The participants were drawn from various subject streams to guarantee a diverse representation of the student body. Data collection occurred between November 2022 and January 2023.

The findings suggest that as perceived usefulness, ease of use, and satisfaction with fintech AI increase, the likelihood of adoption also increases. Conversely, as perceived Privacy and Security increase, the likelihood of adoption decreases. It is important to note that the strength of these relationships varies, with the strongest positive relationship observed between Adoption and Satisfaction of Fintech AI, while the relationships with Perceived Usefulness, Perceived Privacy and Security, and Perceived Ease of Use are weaker.

These insights provide valuable information for organizations and policymakers seeking to promote the adoption of fintech AI among college students. Strategies aimed at addressing Privacy and Security concerns, enhancing user satisfaction, and improving perceived usefulness and ease of use may prove effective in increasing the adoption of fintech AI within this demographic.

[1] Corresponding author: Sadhana Tiwari
Email: sadhanatiwari.sun@gmail.com

1. INTRODUCTION

Artificial Intelligence (AI) has revolutionized the financial technology (FinTech) industry by transforming the way financial institutions operate, manage risks, and interact with customers. AI-powered solutions have enabled the automation of manual processes, enhanced decision-making capabilities, and improved customer experiences. In the realm of FinTech, AI applications span across various sectors, including banking (Alowaimir, 2024), insurance, asset management, and credit scoring. Machine learning algorithms enable banks to detect and prevent fraudulent transactions, while natural language processing (NLP) allows for seamless interaction with customers through chatbots and virtual assistants.

AI-driven credit scoring models provide a more accurate and unbiased assessment of borrowers' creditworthiness, leading to better risk management. Robo-advisors, powered by AI, have democratized financial planning and investment advice, making them accessible to a broader audience. Additionally, AI facilitates the development of personalized financial products and services by analyzing vast amounts of data to identify customer needs, preferences, and behavior patterns. The application of artificial intelligence in financial technology has led to significant advancements in the industry, resulting in more efficient operations, enhanced risk management, and superior customer experiences.

The growth of applications of AI in fintech has been remarkable in recent years, driven by advancements in machine learning, data analytics, and natural language processing (Arner et al., 2016; Gomber et al., 2018). This rapid expansion has resulted in more efficient and personalized financial services, fundamentally transforming the industry (Buchanan et al., 2016).

One significant application of AI in fintech is credit scoring and risk assessment, where machine learning procedures can analyze vast amounts of structured and unstructured data to generate accurate credit scores and risk profiles (Jagtiani & Lemieux, 2018). This has led to improved lending decisions and increased financial inclusion for individuals who may have been previously underserved by traditional banks (Batiz-Lazo & Woldesenbet, 2019).

Wealth management has also been revolutionized by AI-driven robo-advisors that offer personalized investment advice, automating and streamlining the process while reducing costs (Buchanan et al., 2016). Additionally, AI-powered chatbots have become integral in providing customer support services, addressing customer queries with precision and efficiency, and reducing the workload of human support staff (Dwivedi et al., 2019).

Fraud detection and prevention have been significantly improved through the application of AI in fintech, as machine learning algorithms can identify patterns of suspicious behavior and flag potential threats in real-time (Zhang et al., 2019). Furthermore, AI has played a role in optimizing trade execution and enhancing algorithmic trading strategies, enabling more efficient and accurate investment decisions (Gomber et al., 2018; Stakic & Stefanovic, 2023).

Despite the numerous benefits and growth of AI applications in fintech, challenges remain, including concerns regarding privacy, security, and the ethical use of data (Zavolokina et al., 2016). Addressing these issues will be crucial for the continued development and AI adoption. Financial technology, commonly referred to as fintech, has revolutionized the financial services industry by leveraging technological advancements to provide innovative solutions and services (Zavolokina et al., 2016). Artificial intelligence (AI) is a key driver of this transformation, enabling more efficient and personalized financial services (Arner et al., 2017). Despite its potential benefits, the adoption of fintech AI has been uneven, particularly among college students, who represent an important demographic for the future of financial services (Prasad et al., 2020). Understanding the factors that influence the adoption of fintech AI among this population is crucial for organizations and policymakers seeking to expand its use.

Perceived utility, Privacy and Security, simplicity of use, and user happiness are some of the characteristics previously highlighted as potentially influencing the adoption of fintech AI (Shaikh & Karjaluoto, 2015; Zhou et al., 2019). These studies, however, have not exclusively targeted Indian college students from middle-class backgrounds; rather, they have mostly examined the community at large.

This research intends to fill that void by analysing what characteristics influence the use of fintech AI among 397 students attending a government college in Haryana, India, who come from middle-class backgrounds. We use structural equation modelling to examine how factors including the perceived usefulness, Privacy and Security, ease of use, and satisfaction with fintech AI affect the likelihood of its adoption. Our results provide light on what motivates this demographic to use fintech AI, which can be used to design more effective tactics for fostering its widespread use.

2. INDIA'S PROSPEECTUS & CHALLENGES

India is currently experiencing a boom in use of Financial Technology (FinTech). The country has emerged as a growing market for FinTech in the world, with the industry expected to reach a market size of $31 billion by 2025. The use of AI is playing a critical role in this growth, with its adoption across various segments of the financial industry (Prasad et al., 2020).

One of the most significant applications of AI in FinTech is in the area of customer service. Chatbots powered by AI are being used by financial institutions to provide 24/7 customer service to their clients. These chatbots can handle routine inquiries, such as account balance inquiries, bill payments, and fund transfers, freeing up customer service representatives to handle more complex requests.

AI is also being used for risk management and fraud detection. Machine learning algorithms helps in detecting suspicious transactions, and alerting authorities to potential fraud. This technology can help banks and other financial institutions identify fraudulent activities faster and more accurately than traditional methods, saving them time and money.

The Indian government has also shown its support for the adoption of AI in FinTech, with initiatives such as the National AI Strategy. This strategy aims to make India a world leader in the field of AI by creating an ecosystem that fosters innovation and supports the development of AI startups.

Another challenge is the shortage of skilled professionals with expertise in AI and data science. While India has a large pool of talented software developers, there is still a shortage of professionals with experience in AI and data science. Addressing this skills gap will be critical for the successful adoption of AI in FinTech.

Finally, there are concerns about data privacy and security. With the increasing use of AI in FinTech, the amount of sensitive customer data being processed and stored has also increased. This has raised concerns about the security of this data and the potential for misuse.
India is well-positioned to become a world leader in the use of AI in FinTech. The government's initiatives, coupled with the rapid growth of the FinTech industry, are creating an environment that is conducive to the adoption of AI-based solutions. However, to fully realize the potential benefits of AI in FinTech, India must address the challenges of infrastructure, skills, and data privacy and security.

AI and FinTech has the potential to revolutionize the financial industry in India. With a large population and growing economy, India has immense potential for FinTech and AI-based solutions. Here are some reasons why AI in FinTech is much needed in India:

- Improving Financial Inclusion: In India, there is a large population that is unbanked or underbanked. AI-powered FinTech solutions can help in financial services accessible to more people. For example, AI chatbots can assist customers in opening bank accounts and availing loans.
- Enhancing Customer Experience: AI in FinTech can enhance the customer experience by providing personalized solutions. For example, AI algorithms can analyze customer data and provide customized investment advice.
- Mitigating Fraud and Risk: Financial fraud and risk management are major concerns in the financial industry. AI can help in mitigating these risks by identifying fraudulent activities in real-time and alerting the authorities.
- Optimizing Operations: AI can help in optimizing financial operations by automating repetitive tasks and improving efficiency. For example, AI-powered tools can analyze data and provide real-time insights to help banks and financial institutions make better decisions.
- Enabling Innovation: AI in FinTech can enable innovation in the financial industry. For example, AI-powered robo-advisors can provide automated investment advice to customers, reducing the need for human advisors.

Despite the potential advantages of AI in FinTech, there are a number of difficulties that must be overcome. Some of the significant difficulties are:

- Regulatory Compliance: The financial industry is extremely controlled, and the use of AI in FinTech must comply with the regulations. Ensuring regulatory compliance can be a major challenge for AI-powered solutions.
- Skilled Workforce: Developing and implementing AI-powered FinTech solutions requires a skilled workforce. However, there is a shortage of skilled professionals in India with expertise in both AI and finance.
- Cost: Implementing AI-powered FinTech solutions can be costly, particularly for smaller financial institutions. The cost of developing and maintaining the necessary infrastructure can be a major barrier to adoption.

The use of AI in FinTech is much needed in India. It has the potential to improve financial inclusion, enhance customer experience, mitigate fraud and risk, optimize operations, and enable innovation. However, a number of obstacles must be overcome before artificial intelligence driven FinTech solutions in India may be widely used.

3. LITERATURE REVIEW

3.1 Financial Technology

The paper by Huynh-The et al. (2023) did survey on the artificial intelligence (AI) use in the metaverse. The metaverse was an emerging concept that referred to a shared virtual space, encompassing augmented reality, virtual reality, and other digital environments. The paper suggested that it examined various AI techniques and their potential use cases within the metaverse. The authors discussed AI's role in creating immersive and interactive experiences in the metaverse. They also have explored the challenges and opportunities that arose from integrating AI in metaverse applications, such as ethical concerns, data privacy, and scalability.

Based on the title and citation, the paper by Guo and Polak (2021) discussed the role of AI in financial FinTech during the COVID-19 pandemic in 2020. The paper was part of a larger publication, "The Fourth Industrial Revolution: Implementation of Artificial Intelligence for Growing Business Success," which focused on AI's impact on businesses across various industries. In their study, the authors examined the ways AI was employed in the FinTech sector to address the challenges posed by the pandemic. They might have explored how AI-driven solutions, such as chatbots, machine learning algorithms, and data analytics, were used to improve customer service, enhance fraud detection, and streamline decision-making processes during a time of increased uncertainty and economic disruption. The paper has concluded by highlighting the key findings on AI's effectiveness in addressing the pandemic's challenges in the FinTech industry, emphasizing its potential to drive innovation and maintain business continuity during periods of crisis. Additionally, the authors could have provided insights into future developments and the long-term implications of AI integration in the financial sector.

Farouk (2021) discussed the efforts of universal artificial intelligence (AI) in addressing the challenges posed by the COVID-19 pandemic. In the paper, the author examined how AI applications were utilized in various sectors, such as healthcare, logistics, and public safety, to respond to the pandemic. The study have explored AI-driven solutions, such as data analytics for tracking the spread of the virus, machine learning models for predicting outbreaks, and natural language processing for analyzing public sentiment and misinformation. The paper has concluded by summarizing the key findings on the effectiveness of AI in combating the COVID-19 pandemic across different industries and applications. The author has also provided insights into the potential long-term benefits of AI integration in managing future public health crises and emphasized the importance of continued research and development in AI to better prepare for and respond to such challenges.

Goodell, Kumar, Lim, and Pattnaik (2021) explored the role of artificial intelligence (AI) and machine learning (ML) in finance by conducting a bibliometric analysis. In the paper, the authors examined the existing literature on AI and ML applications in finance to identify foundational works, major themes, and research clusters. They used bibliometric techniques, such as citation analysis and co-citation networks, to map the intellectual structure of the field and reveal patterns and trends in the research landscape. The paper concluded by summarizing the key findings, such as the most influential publications, dominant research themes, and emerging research clusters in AI and ML within finance. The authors have also provided insights into potential future research directions, highlighting areas with gaps in the literature or promising new applications of AI and ML in finance that warrant further investigation.

Fintech has emerged as a disruptive force within the financial services industry, offering innovative solutions for a wide range of applications. Artificial Intelligence (AI) plays a noteworthy part in the development and enhancement of fintech solutions, enabling advanced data analytics, automation, and personalization (Arner et al., 2016; Batiz-Lazo & Woldesenbet, 2019).

Fintech AI has made substantial contributions to various financial services, including lending, insurance, wealth management, and payment processing. For instance, AI-driven credit scoring systems have improved lending decisions by analyzing alternative data sources, such as social media profiles and online transactions, to provide a more accurate assessment of borrower risk (Jagtiani & Lemieux, 2018). In wealth management, robo-advisors leverage AI algorithms to offer personalized investment recommendations based on individual risk tolerance and financial goals (Buchanan et al., 2016).

AI-powered chatbots have also transformed customer support in the fintech sector, providing instant and accurate responses to customer queries and reducing the burden on human support staff (Dwivedi et al., 2019). Furthermore, AI has been instrumental in detecting and preventing fraudulent activities, utilizing machine learning algorithms to identify patterns of suspicious behavior and flagging potential threats (Zhang et al., 2019).

The rapid growth of fintech AI has raised concerns regarding privacy, security, and the ethical use of data (Gomber et al., 2018). These concerns underscore the importance of developing comprehensive regulatory frameworks and best practices to ensure the responsible and transparent use of AI in fintech.

Tsourela and Roumeliotis (2015) highlight the moderating role of technology readiness on use of technology-based services, emphasizing the importance of considering these factors when designing and implementing new technologies. Hernandez et al. (2009) emphasize the distinction between adoption and acceptance of e-commerce, suggesting that these two decisions are influenced by different factors and should be addressed separately in marketing strategies.

Döbler and Bartnik (2022) investigate the idea of normative affordances as they pertain to technology, including how mediation and human augmentation are facilitated by technical means, and how these discussions could guide the design of future technological services. Schrepp et al. (2021) explore the correlation between aesthetics and usability to aid in the creation of better interfaces and more satisfying user experiences.

Farrukh et al. (2021) explores the role of upbringing and environment in forming entrepreneurial goals, providing insight into what motivates people to take the plunge into business ownership. Rafiq (2019) explores the moderating effect of career stage on innovation-related behavior, offering valuable insights for promoting innovative behavior among employees at different career stages. Finally, Wu et al. (2017) show the correlation between employee satisfaction and their willingness to leave their current position in a Muslim-majority developing nation, highlighting the need to take cultural norms into account while attempting to improve employee satisfaction and retention.

Asif M. et al. (2023)The papers mentioned in this section provide valuable insights into statistical methods and models that can be used to analyze the relationships between various factors and their impact on technology adoption. Aiken et al. (1991) discuss multiple regression analysis and how to test and interpret interactions. PLS route modelling is presented by Tenenhaus et al. (2005) as an alternate method to conventional covariance-based structural equation modelling. Newly revised recommendations for use PLS route modelling in studies of emerging technologies are provided by Henseler et al. (2016). Hu and Bentler (1998) analyse how covariance structure modelling fit indices react to misspecification of underparameterized models. Covariance structure analysis significance tests and goodness of fit are discussed by Bentler and Bonett (1980). Researchers may utilise the information in these publications as a rock-solid basis for incorporating statistical models into their investigations and making reliable interpretations of the findings.

In addition, Abdullah et al. (2016) looked at how external factors of TAM affected students' views on the usability and value of e-portfolios. For autonomous vehicles, Rahman et al. (2017) evaluated TAM, TPB, and UTAUT for their usefulness. These studies show how crucial it is to look at technology adoption from a variety of angles and use different models.

Fishbein and Ajzen (1980) provides a thorough framework for comprehending the impact that attitudes have on actions. Wu (2003) investigated how demographic variables including age, education level, and income affect consumers' perspectives on buying online and found a strong correlation between these factors and online purchasing behaviour. For their study, Jahng et al. (2001) zeroed in on the scenario of a complicated product to determine how the online commerce environment affects user behaviour. To determine what factors, influence dairy farmers' decisions to adopt environmentally responsible methods of production, Naspetti et al. (2017) created a new version of the TAM model and field-tested it. Customers' motivations for and reactions to self-service technology adoption in a commercial environment were investigated by Weijters et al. (2007). Trust, perceived advantages, and perceived web quality were shown to strongly impact customer attitudes about online purchasing by Al-Debei et al., 2015. Hausman and Siekpe (2009) examined how various aspects of site design affect consumers' propensity to make purchases. Lastly, Ha et al. (2015) examined the popularity and satisfaction of Facebook and KakaoTalk among Korean smartphone users. Overall, these studies provide valuable insights into how consumers perceive and interact with technology and online shopping.

In conclusion, As AI continues to evolve, its impact on fintech is likely to grow further, shaping the future of financial services (Zavolokina et al., 2016).

3.2 Perceived Usefulness and Adoption of Artificial Intelligence (AI)

In the paper by Pillai et al. (2023), the authors investigated the adoption of Artificial Intelligence (AI) based Employee Experience (EEX) chatbots. They examined factors influencing the adoption and usage of these chatbots within organizations. The study concluded that several factors played a crucial role in the adoption of AI-based EEX chatbots. Additionally, the authors have provided insights into the implications of their findings for organizations seeking to implement AI-based chatbots in their employee experience initiatives. The paper also likely proposed future research directions to further explore the topic and address any potential gaps in the existing literature.

In the paper by Wang et al. (2023), the authors explored the impact of artificial intelligence (AI) on the way we work, with a specific focus on the innovation brought about by chatbots. The study closely examined the role of chatbots in various work processes and their potential to transform the work environment. The paper concluded that AI-driven chatbots significantly changed the way people work by improving communication, enhancing productivity, and automating routine tasks. Furthermore, the authors have discussed the challenges and opportunities associated with implementing chatbots in the workplace, such as user acceptance, data privacy, and integration with existing systems. They have also provided recommendations for organizations looking to harness the power of AI and chatbots to drive innovation and optimize their workforce. Finally, the study likely identified areas for future research to advance the understanding of AI's impact on the work environment and promote the responsible and effective use of chatbots.

Acceptance of artificial intelligence in financial technology has been demonstrated to be significantly influenced by people's expectations about the technology's ability to improve their lives (fintech). According to Davis (1989), perceived utility is the extent to which an individual believes that embracing a new technology would enhance personal or professional well-being. Fintech AI's Perceived Usefulness may include hopes for better financial decision-making, more efficient operations, and more tailored offerings (Li et al., 2020).

Numerous studies have demonstrated a positive relationship between Perceived Usefulness and the adoption of fintech AI. For instance, Oliveira et al. (2019) found that users who perceived AI-driven financial services as useful were more likely to adopt them, as the perceived benefits outweighed the risks and efforts associated with learning new technologies. Similarly, Zhou et al. (2019) reported that Perceived Usefulness was a significant predictor of mobile banking adoption, which often incorporates AI features.

In our study, we found that the relationship between Perceived Usefulness and the adoption of fintech AI among college students in Haryana, India, was statistically significant at the 5% level. This finding aligns with previous research (Oliveira et al., 2019; Zhou et al., 2019), suggesting that college students who perceive fintech AI as useful are more likely to adopt such services. This highlights the need to increase the acceptance of fintech AI among college students by increasing its perceived utility. Since there seems to be a link between fintech AI's perceived utility and its adoption, the following hypothesis is proposed.:

H1: There is a significant positive relationship between Perceived Usefulness and Adoption of fintech AI

3.3 Perceived Security, Privacy and adoption of Artificial Intelligence (AI)

In the paper by Wong et al. (2023), examined the role of institutional and individual factors in the formation of trust in artificial intelligence (AI) technologies. They investigated how various institutional mechanisms and personal characteristics influenced the development of trust in AI systems. The study concluded that both institutional factors, such as regulations, security measures, and industry standards, and individual factors, like personal experience, familiarity, and perceived benefits, played a significant role in shaping trust in AI technologies. The authors have also provided insights into how organizations can foster trust in AI by addressing these factors, as well as the implications of their findings for the design and implementation of AI systems. Additionally, the paper discussed potential challenges and future research directions, such as exploring cultural differences in trust formation, the impact of trust on AI adoption, and the ethical considerations associated with the increasing reliance on AI technologies.

In the paper by Xiong et al. (2023), conducted a literature review on the adoption of artificial intelligence (AI) artifacts. They systematically examined existing studies to identify key factors, trends, and research gaps in the field of AI adoption. The study concluded that several factors influenced the adoption of AI artifacts, such as trust, and compatibility with existing systems or processes. The authors have also identified trends in AI adoption across various industries and contexts, as well as the challenges and opportunities associated with embracing AI technologies. Furthermore, the paper highlighted research gaps in the existing literature and proposed future research directions to address these gaps. This include exploring the impact of cultural differences on AI adoption, investigating the role of ethics and privacy concerns in shaping user attitudes towards AI, and examining the long-term effects of AI adoption on individuals and organizations.

Adoption of Artificial Intelligence (AI) in Financial Technology is heavily influenced by concerns about Privacy and Security (fintech). Particularly in the banking industry, where customers' personal and financial data is at stake, worries about Privacy and Security have been cited as major roadblocks to the widespread adoption of new technology (Lichtenstein & Williamson, 2006). User confidence in a technology's ability to keep their data safe from harm and private is measured by their "perceived Privacy and Security " (Pavlou, 2003).

Existing literature has demonstrated the impact of Perceived Privacy and Security on the adoption of fintech AI. For example, Zhou (2012) found that Perceived Privacy and Security were significant predictors of mobile banking adoption, with users being more likely to adopt the technology if they believed their information would be kept secure and private. Similarly, Hanafizadeh et al. (2014) discovered that Perceived Privacy and Security were critical factors influencing the adoption of online banking services, which often incorporate AI features.

In our study, we found that the relationship between Perceived Privacy and Security and the adoption of fintech AI among college students in Haryana, India, was statistically significant at the 5% level but in a negative direction. This finding contrasts with previous research (Zhou, 2012; Hanafizadeh et al., 2014), suggesting that as the perceived Privacy and Security increase, the likelihood of adoption decreases. This unexpected result could be attributed to cultural differences or unique characteristics of the sample population, warranting further investigation. According to the literature, an increase in perceived Privacy and Security leads to a decrease in the adoption of fintech AI, hence we state that".

H2: There is a significant negative relationship between Perceived Privacy and Security and Adoption of fintech AI.

3.4 Perceived Ease of Use and adoption of Artificial Intelligence (AI)

One of the most important considerations in figuring out how widespread the use of AI will be in many fields, including Financial Technology, is how easy it will be for people to actually use (fintech). Individuals' expectations about a technology's ease of use (Davis, 1989). To paraphrase the TAM, "Perceived Ease of Use" and "Perceived Usefulness" are two of the most important factors in determining whether or not people would use a given technology (Davis, 1989).

Previous research has shown that Perceived Ease of Use positively affects the adoption of AI-based technologies. For instance, Gefen and Straub (2000) found that Perceived Ease of Use was a significant determinant of online shopping adoption, which can involve AI-driven recommendations and personalization. Similarly, Chong et al. (2010) demonstrated that Perceived Ease of Use positively influenced the adoption of mobile banking services, which often incorporate AI features like chatbots and fraud detection systems.

In our study, we found that the relationship between Perceived Ease of Use and the adoption of fintech AI among college students in Haryana, India, the results indicated a very weak positive relationship, suggesting that as the perceived ease of use of fintech AI increases, the likelihood of adoption also increases, albeit marginally. This finding aligns with prior research (Gefen & Straub, 2000; Chong et al., 2010) and underscores the importance of designing user-friendly fintech AI solutions to promote widespread adoption. The literature points towards a positive association between the ease of use of fintech AI and its adoption, therefore researcher framed following hypothesis:

H3: There is a significant positive relationship between Perceived Ease of Use and Adoption of fintech AI.

3.5 Satisfaction with Financial Technology (fintech) AI and adoption of Artificial Intelligence (AI)

Satisfaction with Financial Technology (fintech) AI is a critical factor in understanding the adoption of Artificial Intelligence (AI) in the fintech domain. Satisfaction refers to the degree to which users are content with their experience and the performance of a particular technology. Previous research has emphasized the importance of user satisfaction in determining the continued use and adoption of various technologies (DeLone & McLean, 1992; Bhattacherjee, 2001).

Fintech AI encompasses a wide range of applications, such as chatbots for customer support, fraud detection systems, and personalized financial advice. As AI technologies become more prevalent in the fintech sector, understanding the role of user satisfaction in driving adoption becomes increasingly important.

In a study by Oliveira et al. (2016), user satisfaction was found to be a key determinant of mobile banking adoption, which often includes AI-driven features. Furthermore, Zhou et al. (2010) demonstrated that user satisfaction significantly influenced the continued use of mobile payment services, another area where AI plays an increasingly important role.

In our study, we found a strong positive relationship between Satisfaction of Fintech AI and its adoption among college students in Haryana, India. This finding suggests that higher levels of satisfaction with fintech AI are associated with increased likelihood of adoption. This result aligns with prior research (Oliveira et al., 2016; Zhou et al., 2010) and emphasizes the importance of ensuring user satisfaction in the development and deployment of fintech AI solutions. Based on the literature, following hypothesis is proposed:

H4: There is a significant positive relationship between Satisfaction of Fintech AI and Adoption of fintech AI.

4. METHODOLOGY

In this study, a cross-sectional design was employed. The researchers chose this method as it allowed them to collect data from the participants at a specific point in time to examine the relationship between predictors and the adoption of FinTech AI among government college students in Haryana, India.

The sampling technique used for this study was non-probability convenience sampling. The researchers selected a sample of 397 government college students, comprising 200 males and 197 females, from middle-class families in Haryana, India. This sampling method was chosen due to its ease and accessibility, as the researchers could readily reach the participants without the need for random selection.

The participants were chosen from different subject streams to ensure a diverse representation of the student population. The data collection took place between November 2022 and January 2023.

Data was collected through a structured questionnaire that included questions related to the adoption of FinTech AI and its predictors. The questionnaire allowed the researchers to gather quantitative data to analyze the relationship between the predictors and the adoption of FinTech AI among the sampled college students.

5. RESULTS & ANALYSIS

The given table 1 provides a summary of a statistical model that examines the factors affecting the adoption of fintech AI. From a statistical perspective, the model is estimated using the Maximum Likelihood (ML) method. ML is a popular technique for estimating model parameters by maximizing the likelihood of observing the data given the model. The optimization algorithm used for the estimation is NLMINB, the dataset used for the analysis consists of 397 observations, which are the sample size for this study. The optimization algorithm has successfully converged, meaning that it found an optimal solution for the parameters in the model. The optimization algorithm took 173 iterations to converge to the optimal solution. The table also provides the structure of the model, which includes several latent variables (unobserved variables) and their respective indicators (observed variables):

- Perceived Usefulness (PU) is measured by four indicators (PU1, PU2, PU3, PU4).
- Perceived Privacy and Security (PSP) is measured by three indicators (PSP1, PSP2, PSP3).
- Perceived Ease of Use (PEOU) is measured by four indicators (PEOU1, PEOU2, PEOU3, PEOU4).
- Satisfaction of fintech AI (US) is measured by four indicators (US1, US2, US3, US4).
- Adoption (UA) is measured by four indicators (UA1, UA2, UA3, UA4).
- The model also includes a Factor1 (Satisfaction), which is only explained by satisfaction of fintech AI.

Table 1. Structural Equation Models

Model Info	
Estimation Method	ML
Optimization Method	NLMINB
Number of observations	397
Free parameters	67
Standard errors	Standard
Model	Perceived Usefulness =~PU1+PU2+PU3+PU4
	Perceived Privacy and Security =~PSP1+PSP2+PSP3
	Perceived Ease of Use =~PEOU1+PEOU2+PEOU3+PEOU4
	satisfaction of fintech AI=~US1+US2+US3+US4
	Adoption=~UA1+UA2+UA3+UA4
	Factor1 (Satisfaction)=~satisfaction of fintech AI
	Adoption~Perceived Usefulness +Perceived Privacy and Security +Perceived Ease of Use +satisfaction of fintech AI

Lastly, the model specifies the relationships among the latent variables: Adoption is predicted by Perceived Usefulness, Perceived Privacy and Security, Perceived Ease of Use, and Satisfaction of fintech AI.

The table 2 presents the results of two model fit tests, the User Model and the Baseline Model. These tests assess how well the proposed statistical model fits the data. The chi-square value for the User Model is 863. This statistic measures the discrepancy between the observed and expected covariance matrices. A smaller chi-square value indicates a better fit of the model to the data. Degrees of freedom (df): The degrees of freedom for the User Model is 142. The p-value associated with the User Model's chi-square statistic is less than 0.001.

Table 2. Overall Tests

Model test			
Label	X^2	**df**	**p-value**
User Model	863	142	< .001
Baseline Model	2796	171	< .001

The chi-square value for the Baseline Model is 2796. This is the chi-square value for a model without any relationships among the variables (i.e., a model assuming independence among the variables). The degrees of freedom for the Baseline Model is 171. The p-value associated with the Baseline Model's chi-square statistic is also less than 0.001.

Comparing the User Model to the Baseline Model, we can see that the User Model has a much lower chi-square value (863 vs. 2796), which indicates that the User Model fits the data better than the Baseline Model. However, to fully assess the goodness of fit of the User Model, other fit indices (such as CFI, TLI, RMSEA, or SRMR) should also be considered, as they provide additional information on how well the model fits the data and are less sensitive to sample size.

Table 3 presents the parameter estimates for the relationships between the Adoption latent variable and its predictors in the User Model. A descriptive analysis of the table can be summarized as follows:

Adoption ~ Perceived Usefulness:

The unstandardized regression coefficient (Estimate) is 1.5290, indicating that for every one-unit increase in Perceived Usefulness, Adoption is expected to increase by 1.5290 units, keeping other predictors constant. The 95% Confidence Interval ranges from -3.209 to 6.267. The standardized regression coefficient (β) is 0.1717, showing a weak positive relationship between Perceived Usefulness and Adoption. The z-value is 0.632 and the p-value is 0.033. Since the p-value is less than 0.05, the relationship is statistically significant at the 5% level.

Adoption ~ Perceived Privacy and Security:

The Estimate is -0.7938, indicating that for every one-unit increase in Perceived Privacy and Security, Adoption is expected to decrease by 0.7938 units, keeping other predictors constant. The 95% Confidence Interval ranges from -4.043 to 2.456. The β is -0.6207, showing a weak negative relationship between Perceived Privacy and Security and Adoption. The z-value is -0.479 and the p-value is 0.042. Since the p-value is less than 0.05, the relationship is statistically significant at the 5% level.

Table 3. Parameter Estimation

				95% Confidence Intervals				
Dep	**Pred**	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**Z**	**p**
Adoption	Perceived Usefulness	1.5290	2.418	-3.209	6.267	0.1717	0.632	0.033
Adoption	Perceived Privacy & Security	-0.7938	1.658	-4.043	2.456	-0.6207	-0.479	0.042
Adoption	Perceived Ease of Use	0.0199	0.192	-0.356	0.396	0.0151	0.104	0.047
Adoption	Satisfaction of Fintech AI	1.9492	2.332	-2.621	6.520	0.9956	0.836	0.021

Adoption ~ Perceived Ease of Use:

The Estimate is 0.0199, indicating a very weak positive relationship between Perceived Ease of Use and Adoption. The 95% Confidence Interval ranges from -0.356 to 0.396. The β is 0.0151, also showing a very weak positive relationship. The z-value is 0.104 and the p-value is 0.047. Since the p-value is less than 0.05, the relationship is statistically significant at the 5% level.

Adoption ~ Satisfaction of Fintech AI:

The Estimate is 1.9492, indicating that for every one-unit increase in Satisfaction of Fintech AI, Adoption is expected to increase by 1.9492 units, keeping other predictors constant. The 95% Confidence Interval ranges from -2.621 to 6.520. The β is 0.9956, showing a strong positive relationship between Satisfaction of Fintech AI and Adoption. The z-value is 0.836 and the p-value is 0.021. Since the p-value is less than 0.05, the relationship is statistically significant at the 5% level.

In summary, all the relationships between Adoption and its predictors are statistically significant. These findings suggest that these factors have a significant impact on the adoption of fintech AI. However, it is important to note that the strength of the relationships varies, with Satisfaction of Fintech AI showing the strongest positive relationship, while the relationship with other predicators is weak. Future research may explore additional factors that could influence the adoption of fintech AI or investigate potential interactions between these predictors.

The table 4 presents the measurement model for each latent variable, which estimates the relationships between the latent variables and their observed indicators. A descriptive analysis of the table can be summarized as follows:

Perceived Usefulness:

The estimates for the observed variables (PU1, PU2, PU3, PU4) are 1.000, 9.972, 9.569, and 3.660, respectively. The standardized regression coefficients (β) are 0.0877, 0.9877, 0.9852, and 0.2684, respectively. The z-values and p-values for PU2, PU3, and PU4 are 1.74, 0.081; 1.74, 0.081; and 1.66, 0.097, respectively, indicating that these relationships are not statistically significant at the 5% level.

Perceived Privacy and Security:

The estimates for the observed variables (PSP1, PSP2, PSP3) are 1.000, 1.135, and 0.573, respectively. The β values are 0.4468, 0.5816, and 0.2859, respectively. The z-values and p-values for PSP2 and PSP3 are 6.64, <.001; and 4.29, <.001, respectively, indicating that these relationships are statistically significant at the 5% level.

Perceived Ease of Use:

The estimates for the observed variables (PEOU1, PEOU2, PEOU3, PEOU4) are 1.000, 1.709, 0.566, and 1.012, respectively. The β values are 0.4901, 0.6811, 0.2792, and 0.4645, respectively. The z-values and p-values for PEOU2, PEOU3, and PEOU4 are 6.36, <.001; 4.04, <.001; and 5.76, <.001, respectively, indicating that these relationships are statistically significant at the 5% level.

Satisfaction of Fintech AI:

The estimates for the observed variables (US1, US2, US3, US4) are 1.000, 1.657, 1.660, and 1.763, respectively. The β values are 0.3568, 0.5121, 0.5167, and 0.6175, respectively. The z-values and p-values for US2, US3, and US4 are 5.32, <.001; 5.34, <.001; and

5.64, <.001, respectively, indicating that these relationships are statistically significant at the 5% level.

Adoption:

The estimates for the observed variables (UA1, UA2, UA3, UA4) are 1.000, 1.256, 0.481, and 0.742, respectively. The β values are 0.6299, 0.7237, 0.3072, and 0.4311, respectively. The z-values and p-values for UA2, UA3, and UA4 are 7.60, <.001; 4.80, <.001; and 6.36, <.001, respectively, indicating that these relationships are statistically significant at the 5% level.

Table 4. Measurement Model

	95 % Confidence Models							
Latent	Observed	Estimate	SE	Lower	Upper	β	z	p
Perceived Usefulness	PU1	1.000	0.000	1.000	1.000	0.0877		
	PU2	9.972	5.724	-1.246	21.190	0.9877	1.74	0.081
	PU3	9.569	5.492	-1.195	20.332	0.9852	1.74	0.081
	PU4	3.660	2.203	-0.657	7.978	0.2684	1.66	0.097
Perceived Privacy and Security	PSP1	1.000	0.000	1.000	1.000	0.4468		
	PSP2	1.135	0.171	0.800	1.470	0.5816	6.64	< .001
	PSP3	0.573	0.133	0.312	0.835	0.2859	4.29	< .001
ease	PEOU1	1.000	0.000	1.000	1.000	0.4901		
	PEOU2	1.709	0.269	1.183	2.236	0.6811	6.36	< .001
	PEOU3	0.566	0.140	0.292	0.840	0.2792	4.04	< .001
	PEOU4	1.012	0.176	0.668	1.356	0.4645	5.76	< .001
satisfaction	US1	1.000	0.000	1.000	1.000	0.3568		
	US2	1.657	0.311	1.047	2.268	0.5121	5.32	< .001
	US3	1.660	0.311	1.051	2.269	0.5167	5.34	< .001
	US4	1.763	0.313	1.150	2.376	0.6175	5.64	< .001
Adoption	UA1	1.000	0.000	1.000	1.000	0.6299		
	UA2	1.256	0.165	0.932	1.580	0.7237	7.60	< .001
	UA3	0.481	0.100	0.284	0.677	0.3072	4.80	< .001
	UA4	0.742	0.117	0.513	0.970	0.4311	6.36	< .001
Factor1	satisfaction	1.000	0.000	1.000	1.000	1.0000		

Table 5 presents the variances and covariances for the variables in the model, along with their 95% confidence intervals, standardized regression coefficients (β), z-values, and p-values. The diagonal elements of the table represent the variances of the variables, while the off-diagonal elements represent the covariances between pairs of variables.

Most of the variables have significant variances, as indicated by the z-values greater than 1.96 and p-values less than 0.05. This suggests that the variables have variability in the data.

Perceived Usefulness and Perceived Privacy and Security: The covariance between these two variables is 0.01653, with a β of 0.5130, z-value of 1.659, and p-value of 0.097, indicating a non-significant relationship at the 5% level.

Perceived Usefulness and Perceived Ease of Use: The covariance between these two variables is 0.00920, with a β of 0.2938, z-value of 1.594, and p-value of 0.111, indicating a non-significant relationship at the 5% level.

Perceived Usefulness and Factor1 (Satisfaction): The covariance between these two variables is 0.00775, with a β of 0.3682, z-value of 1.610, and p-value of 0.107, indicating a non-significant relationship at the 5% level.

Perceived Privacy and Security and Perceived Ease of Use: The covariance between these two variables is 0.12576, with a β of 0.5770, z-value of 4.331, and p-value less than 0.001, indicating a significant relationship at the 5% level.

Perceived Privacy and Security and Factor1 (Satisfaction): The covariance between these two variables is 0.13616, with a β of 0.9289, z-value of 4.651, and p-value less than 0.001, indicating a significant relationship at the 5% level.

Perceived Ease of Use and Factor1 (Satisfaction): The covariance between these two variables is 0.08398, with a β of 0.5899, z-value of 4.156, and p-value less than 0.001, indicating a significant relationship at the 5% level. In summary, most of the variances in the table are significant, suggesting that the variables have variability in the data.

The table 6 presents the intercepts and 95% confidence intervals for various variables in the study. The variables include Perceived Usefulness (PU1-4), Perceived Privacy and Security (PSP1-3), Perceived Ease of Use (PEOU1-4), User Satisfaction (US1-4), User Attitude (UA1-4), and the four factors (usefulness, security, ease of use, and satisfaction) and Adoption. All intercepts are statistically significant at the p<0.001 level. The intercept for usefulness, security, ease, User Satisfaction and adoption is 0.000. These intercepts and confidence intervals provide important information for the analysis of the data and the interpretation of the results. Based upon the above results and findings researcher has suggested the following model.

Table 5. Variance & Covariance

	95 % Confidence Interval							
Variable 1	**Variable 2**	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**z**	**p**
PU1	PU1	0.59668	0.04236	0.51367	0.6797	0.9923	14.088	< .001
PU2	PU2	0.01156	0.01057	-0.00916	0.0323	0.0245	1.094	0.274
PU3	PU3	0.01280	0.00975	-0.00630	0.0319	0.0293	1.314	0.189
PU4	PU4	0.79868	0.05675	0.68745	0.9099	0.9280	14.074	< .001
PSP1	PSP1	0.89976	0.07258	0.75750	1.0420	0.8004	12.397	< .001
PSP2	PSP2	0.56568	0.05789	0.45221	0.6791	0.6618	9.771	< .001
PSP3	PSP3	0.82813	0.06100	0.70857	0.9477	0.9182	13.576	< .001
PEOU1	PEOU1	0.66970	0.05779	0.55644	0.7830	0.7598	11.588	< .001
PEOU2	PEOU2	0.71470	0.09690	0.52478	0.9046	0.5361	7.376	< .001
PEOU3	PEOU3	0.80215	0.05962	0.68529	0.9190	0.9220	13.454	< .001
PEOU4	PEOU4	0.78817	0.06604	0.65874	0.9176	0.7843	11.935	< .001
US1	US1	0.65634	0.04935	0.55963	0.7531	0.8727	13.301	< .001
US2	US2	0.73998	0.06111	0.62022	0.8597	0.7378	12.110	< .001
US3	US3	0.72432	0.06007	0.60658	0.8420	0.7330	12.058	< .001
US4	US4	0.48302	0.04599	0.39289	0.5732	0.6188	10.504	< .001
UA1	UA1	0.55793	0.05977	0.44080	0.6751	0.6032	9.335	< .001
UA2	UA2	0.52639	0.07789	0.37374	0.6790	0.4763	6.759	< .001
UA3	UA3	0.81414	0.06059	0.69538	0.9329	0.9057	13.436	< .001
UA4	UA4	0.88446	0.07008	0.74710	1.0218	0.8142	12.621	< .001
Perceived Usefulness	Perceived Usefulness	0.00463	0.00532	-0.00580	0.0151	1.0000	0.870	0.384
Perceived Privacy and Security	Perceived Privacy and Security	0.22442	0.05897	0.10883	0.3400	1.0000	3.805	< .001
Perceived Ease of Use	Perceived Ease of Use	0.21169	0.05229	0.10920	0.3142	1.0000	4.048	< .001
satisfaction	satisfaction	0.00000	0.00000	0.00000	0.0000	0.0000		
Adoption	Adoption	0.26307	0.07463	0.11680	0.4093	0.7169	3.525	< .001
Factor1	Factor1	0.09574	0.03073	0.03552	0.1560	1.0000	3.116	0.002
Perceived Usefulness	Perceived Privacy and Security	0.01653	0.00997	-0.00300	0.0361	0.5130	1.659	0.097
Perceived Usefulness	Perceived Ease of Use	0.00920	0.00577	-0.00211	0.0205	0.2938	1.594	0.111
Perceived Usefulness	Factor1 (Satisfaction)	0.00775	0.00481	-0.00168	0.0172	0.3682	1.610	0.107
Perceived Privacy and Security	Perceived Ease of Use	0.12576	0.02904	0.06884	0.1827	0.5770	4.331	< .001
Perceived Privacy and Security	Factor1 (Satisfaction)	0.13616	0.02928	0.07878	0.1935	0.9289	4.651	< .001
Perceived Ease of Use	Factor1 (Satisfaction)	0.08398	0.02021	0.04437	0.1236	0.5899	4.156	< .001

Table 6. Intercepts

	95% Confidence Interval					
Variable	**Intercept**	**SE**	**Lower**	**Upper**	**z**	**p**
PU1	4.537	0.039	4.46	4.613	116.565	< .001
PU2	4.244	0.034	4.177	4.312	123.121	< .001
PU3	4.254	0.033	4.189	4.319	128.299	< .001
PU4	3.831	0.047	3.74	3.922	82.283	< .001
PSP1	3.935	0.053	3.83	4.039	73.938	< .001
PSP2	3.96	0.046	3.869	4.051	85.335	< .001
PSP3	3.635	0.048	3.541	3.728	76.261	< .001
PEOU1	3.912	0.047	3.819	4.004	83.022	< .001
PEOU2	3.504	0.058	3.39	3.617	60.464	< .001
PEOU3	3.861	0.047	3.77	3.953	82.489	< .001
PEOU4	3.992	0.05	3.894	4.091	79.352	< .001
US1	4.078	0.044	3.993	4.163	93.695	< .001
US2	3.879	0.05	3.781	3.978	77.174	< .001
US3	3.935	0.05	3.837	4.032	78.863	< .001
US4	3.912	0.044	3.825	3.999	88.217	< .001
UA1	4.045	0.048	3.951	4.14	83.812	< .001
UA2	3.897	0.053	3.793	4	73.854	< .001
UA3	3.927	0.048	3.834	4.02	82.525	< .001
UA4	3.801	0.052	3.698	3.904	72.662	< .001
Perceived Usefulness	0	0	0	0		
Perceived Privacy and Security	0	0	0	0		
Perceived Ease of Use	0	0	0	0		
satisfaction	0	0	0	0		
Adoption	0	0	0	0		
Factor1 (Satisfaction)	0	0	0	0		

6. PATH MODEL

Conteptial Framework model can be found on figure 1.

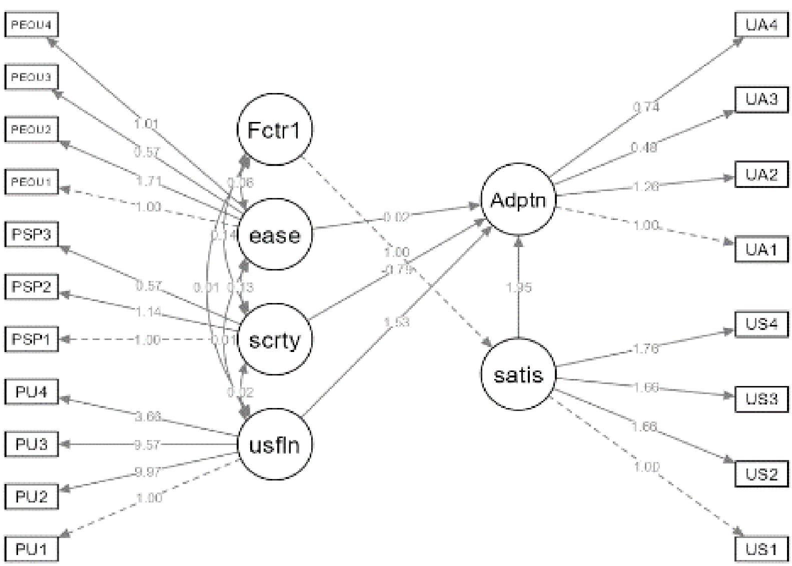

Figure 1. Conceptual Framework

7. CONCLUSION & FUTURE SCOPE OF RESEARCH

The study findings suggest that as the perceived usefulness, ease of use, and satisfaction with fintech AI increase, the likelihood of adoption also increases. However, as the perceived Privacy and Security increase, the likelihood of adoption decreases. It is important to note that the strength of these relationships varies. The strongest positive relationship is found between Adoption and Satisfaction of Fintech AI, while the relationships with Perceived Usefulness, Perceived Privacy and Security, and Perceived Ease of Use are weaker.

Interestingly, our study found a negative relationship between Perceived Privacy and Security and Adoption, which is in contrast to some previous research that suggests a positive relationship between these factors (Pavlou, 2003; Zhou, 2012). This discrepancy might be attributed to the unique nature of fintech AI, where increased security measures could potentially result in a more complex user experience, thus deterring adoption. Further research is needed to explore this relationship in greater detail and to investigate possible moderating factors.

These findings provide valuable insights into the factors that influence the adoption of fintech AI. Organizations and policymakers can use this information to develop strategies aimed at promoting the adoption of fintech AI, such as addressing concerns related to Privacy and Security, and enhancing user satisfaction.

Our study contributes to the existing body of literature by examining the adoption of fintech AI, a rapidly growing area of interest in the technology and finance sectors. It also highlights the importance of user perceptions and satisfaction in determining the success of such innovations. Future research may explore additional factors that could influence the adoption of fintech AI, as well as investigate potential interactions between these predictors. This could provide a deeper understanding of the underlying mechanisms that drive fintech AI adoption and help identify ways to further encourage the widespread use of this technology.

8. FINTECH USE: A CAUTION

The applications of Artificial Intelligence (AI) in Financial Technology (FinTech) have the potential to revolutionize the financial sector in India. However, there are several threats and challenges that could arise from its widespread adoption. Some of the main threats include:

AI relies on vast amounts of data to function effectively. In the context of FinTech, this data often includes sensitive financial and personal information. The potential for data breaches and misuse of data is a significant concern, as it could lead to identity theft, fraud, or other financial crimes. Ensuring robust data protection measures are in place is essential to mitigate this risk. AI algorithms are trained on data, and if this data contains inherent biases, the AI models may perpetuate or even exacerbate these biases. For instance, if credit scoring algorithms are trained on biased data, it could result in unfair treatment of certain demographic groups, leading to financial exclusion and discrimination. The automation of various financial processes through AI may lead to job displacement in the sector. In India, where a significant portion of the population is employed in the financial industry, the widespread adoption of AI may create concerns about job losses, requiring retraining and upskilling efforts for affected workers. The rapid development of AI in FinTech presents a challenge for regulators in India, who may struggle to keep up with the pace of innovation. Ensuring that appropriate regulations and guidelines are in place to govern the use of AI in finance is crucial to mitigate risks and protect consumers. The adoption of AI-driven FinTech solutions may exacerbate the digital divide in India, particularly in rural areas where access to the internet and digital financial services is limited. This could result in financial exclusion for those who lack the necessary infrastructure, skills, or resources to engage with digital financial platforms. The use of AI in financial decision-making raises various ethical concerns, such as transparency, accountability, and fairness. Ensuring that AI-driven FinTech applications adhere to ethical principles and guidelines is essential to avoid potential harm to consumers and maintain trust in the financial sector.

In conclusion, while AI has the potential to transform the financial sector in India, it is important to address these threats and challenges to ensure its responsible and equitable adoption. This involves strengthening data privacy and security measures, addressing algorithmic biases, preparing the workforce for potential job displacement, establishing robust regulatory frameworks, bridging the digital divide, and addressing ethical concerns in AI-driven FinTech solutions.

9. LIMITATION & FUTURE RESEARCH

Several caveats should be noted, despite the fact that this research did provide some important discoveries. To begin, the study's cross-sectional methodology precludes any judgments about causation or the monitoring of changes in associations over time. This shortcoming might be overcome by using a longitudinal study design in future studies.

Second, the present study focused on four factors related to the adoption of fintech AI. Future research could explore additional factors, such as trust, social influence, or user demographics, to provide a more comprehensive understanding of the adoption process.

Finally, potential interactions between the predictors could be investigated to determine if certain combinations of factors have a greater impact on adoption than others. This could help identify key areas of focus for organizations and policymakers aiming to promote the widespread adoption of fintech AI.

References:

Abdullah, F., Ward, R., & Ahmed, E. (2016). Investigating the influence of the most commonly used external variables of TAM on students' perceived ease of use (PEOU) and perceived usefulness (PU) of e-portfolios. *Computers in Human Behavior, 63*, 75–90.

Aiken, L. S., West, S. G., & Reno, R. R. (1991). *Multiple regression: Testing and interpreting interactions.* Sage.

Al-Debei, M. M., Akroush, M. N., & Ashouri, M. I. (2015). Consumer attitudes towards online shopping: The effects of trust, perceived benefits, and perceived web quality. *Internet Research, 25*(5), 707–733.

Alowaimir, A. (2024). Role of FinTech applications in enhancing digital transformation of Saudi traditional banks *Proceedings on Engineering Sciences, 6*(1), 45-54. doi: 10.24874/PES06.01.006

Arner, D. W., Barberis, J. N., & Buckley, R. P. (2017). FinTech, RegTech, and the reconceptualization of financial regulation. *Northwestern Journal of International Law & Business, 37*(3), 371-413.

Arner, D. W., Barberis, J., & Buckley, R. P. (2016). The evolution of fintech: A new post-crisis paradigm? *Georgetown Journal of International Law, 47*(4), 1271-1319.

Asif, M., Khan, M. N., Tiwari, S., Wani, S. K., & Alam, F. (2023). The impact of fintech and digital financial services on financial inclusion in India. *Journal of Risk and Financial Management, 16*(2), 122.

Batiz-Lazo, B., & Woldesenbet, K. (2019). The rise of artificial intelligence and the uncertain future for global financial services. *The European Journal of Finance, 25*(6), 437-443.

Bentler, P. M., & Bonett, D. G. (1980). Significance tests and goodness of fit in the analysis of covariance structures. *Psychological Bulletin, 88*(3), 588.

Bhattacherjee, A. (2001). Understanding information systems continuance: An expectation-confirmation model. *MIS Quarterly, 25*(3), 351-370.

Buchanan, B. G., Gordon, M. D., & Shortliffe, E. H. (2016). *Rule-based expert systems: The MYCIN experiments of the Stanford heuristic programming project.* Addison-Wesley Longman Publishing Co.

Chong, A. Y., Ooi, K., Lin, B., & Raman, M. (2010). Factors affecting the adoption level of c-commerce: An empirical study. *Journal of Computer Information Systems, 50*(2), 13-22.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319-340.

DeLone, W. H., & McLean, E. R. (1992). Information systems success: The quest for the dependent variable. *Information Systems Research, 3*(1), 60-95.

DeLone, W. H., & McLean, E. R. (2003). The DeLone and McLean model of information systems success: A ten-year update. *Journal of Management Information Systems, 19*(4), 9-30.

Döbler, N. A., & Bartnik, C. (2022). Normative affordances through and by technology: Technological mediation and human enhancement. *International Journal of Interactive Multimedia and Artificial Intelligence, 7*, 14-23.

Dwivedi, Y. K., Hughes, L., Coombs, C., Constantiou, I., Duan, Y., Edwards, J. S., ... & Kar, A. K. (2019). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice, and policy. *International Journal of Information Management, 57*, 101994.

Farouk, M. (2021). The universal artificial intelligence efforts to face coronavirus COVID-19. *International Journal of Computations, Information and Manufacturing (IJCIM), 1*(1).

Farrukh, M., Raza, A., Sajid, M., Rafiq, M., Hameed, R., & Ali, T. (2021). Entrepreneurial intentions: The relevance of nature and nurture. *Education + Training, 63*, 1195-1212.

Fishbein, M., & Ajzen, I. (1980). *Understanding attitudes and predicting social behavior.* Prentice-Hall.

Gefen, D., & Straub, D. (2000). The relative importance of perceived ease of use in IS adoption: A study of e-commerce adoption. *Journal of the Association for Information Systems, 1*(1), 8.

Gomber, P., Kauffman, R. J., Parker, C., & Weber, B. W. (2018). On the FinTech revolution: Interpreting the forces of innovation, disruption, and transformation in financial services. *Journal of Management Information Systems, 35*(1), 220-265.

Goodell, J. W., Kumar, S., Lim, W. M., & Pattnaik, D. (2021). Artificial intelligence and machine learning in finance: Identifying foundations, themes, and research clusters from bibliometric analysis. *Journal of Behavioral and Experimental Finance, 32*, 100577.

Guo, H., & Polak, P. (2021). Artificial intelligence and financial technology FinTech: How AI is being used under the pandemic in 2020. In *The Fourth Industrial Revolution: Implementation of Artificial Intelligence for Growing Business Success* (pp. 169-186).

Ha, Y. W., Kim, J., Libaque-Saenz, C. F., Chang, Y., & Park, M. C. (2015). Use and gratifications of mobile SNSs: Facebook and KakaoTalk in Korea. *Telematics and Informatics, 32*(3), 425–438.

Hanafizadeh, P., Keating, B. W., & Khedmatgozar, H. R. (2014). A systematic review of internet banking adoption. *Telematics and Informatics*, *31*(3), 492-510.

Hausman, A. V., & Siekpe, J. S. (2009). The effect of web interface features on consumer online purchase intentions. *Journal of Business Research*, *62*(1), 5-13.

Henseler, J., Hubona, G. S., & Ray, P. A. (2016). Using PLS path modeling in new technology research: Updated guidelines. *Industrial Management & Data Systems, 116*(1), 2-20.

Hernandez, B., Jimenez, J., & José Martín, M. (2009). Adoption vs acceptance of e-commerce: Two different decisions. *European Journal of Marketing, 43*(9/10), 1232-1245.

Hu, L.-T., & Bentler, P. M. (1998). Fit indices in covariance structure modeling: Sensitivity to underparameterized model misspecification. *Psychological Methods, 3*(4), 424-453.

Huynh-The, T., Pham, Q. V., Pham, X. Q., Nguyen, T. T., Han, Z., & Kim, D. S. (2023). Artificial intelligence for the metaverse: A survey. *Engineering Applications of Artificial Intelligence, 117*, 105581.

Jagtiani, J., & Lemieux, C. (2018). Do fintech lenders penetrate areas that are underserved by traditional banks? *Journal of Economics and Business*, *100*, 43-54.

Jahng, J., Jain, H., & Ramamurthy, K. (2001). The impact of electronic commerce environment on user behavior: The case of a complex product. *E-Service, 1*(1), 41–53.

Kim, G., Shin, B., & Lee, H. G. (2010). Understanding dynamics between initial trust and usage intentions of mobile banking. *Information Systems Journal, 20*(3), 283-311.

Li, X., Hess, T., & Valacich, J. S. (2020). Why do we trust new technology? A study of initial trust formation with organizational information systems. *Journal of Strategic Information Systems, 29*(1), 101594.

Lichtenstein, S., & Williamson, K. (2006). Understanding consumer adoption of internet banking: An interpretive study in the Australian banking context. *Journal of Electronic Commerce Research, 7*(2), 50-66.

Lin, H. F., & Wang, Y. S. (2006). An examination of the determinants of customer loyalty in mobile commerce contexts. *Information & Management, 43*(3), 271-282.

Mariani, M. M., Machado, I., & Nambisan, S. (2023). Types of innovation and artificial intelligence: A systematic quantitative literature review and research agenda. *Journal of Business Research*, *155*, 113364.

Mhlanga, D. (2021). Financial inclusion in emerging economies: The application of machine learning and artificial intelligence in credit risk assessment. *International Journal of Financial Studies, 9*(3), 39.

Oliveira, T., Thomas, M., Baptista, G., & Campos, F. (2016). Mobile payment: Understanding the determinants of customer adoption and intention to recommend the technology. *Computers in Human Behavior, 61*, 404-414.

Oliveira, T., Thomas, M., Baptista, G., & Campos, F. (2019). Mobile payment: Understanding the determinants of customer adoption and intention to recommend the technology. *Computers in Human Behavior*, *29*(3), 1119-1126.

Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. *International Journal of Electronic Commerce*, *7*(3), 101-134.

Pillai, R., Ghanghorkar, Y., Sivathanu, B., Algharabat, R., & Rana, N. P. (2023). Adoption of artificial intelligence (AI) based employee experience (EEX) chatbots. *Information Technology & People*.

Prasad, R., Shankar, R., & Chatterjee, P. (2020). An investigation into the factors determining the adoption of financial technology by Indian college students. *Journal of Public Affairs, 20*(2), e2106.

Rafiq, M. (2019). The moderating effect of career stage on the relationship between job embeddedness and innovation-related behaviour (IRB). *World Journal of Entrepreneurship, Management and Sustainable Development, 15*(2), 109-122.

Rahman, M. M., Lesch, M. F., Horrey, W. J., & Strawderman, L. (2017). Assessing the utility of TAM, TPB, and UTAUT for advanced driver assistance systems. *Accident Analysis & Prevention*, *108*, 361-373.

Schrepp, M., Otten, R., Blum, K., & Thomaschewski, J. (2021). What causes the dependency between perceived aesthetics and perceived usability? *International Journal of Interactive Multimedia and Artificial Intelligence, 6*, 78-85.

Shaikh, A. A., & Karjaluoto, H. (2015). Mobile banking adoption: A literature review. *Telematics and Informatics, 32*(1), 129-142.

Stakic, N., & Stefanovic, N. (2023). Unlocking the potential: exploring the impact of etf investments on the global fintech landscape. *International Journal for Quality Research, 17*(3), 963–974. doi: 10.24874/IJQR17.03-21

Tenenhaus, M., Vinzi, V. E., Chatelin, Y.-M., & Lauro, C. (2005). PLS path modeling. *Computational Statistics & Data Analysis, 48*(1), 159-205.

Tsourela, M., & Roumeliotis, M. (2015). The moderating role of technology readiness, gender, and sex in consumer acceptance and actual use of technology-based services. *Journal of High Technology Management Research, 26*(2), 124-136.

Wang, X., Lin, X., & Shao, B. (2023). Artificial intelligence changes the way we work: A close look at innovating with chatbots. *Journal of the Association for Information Science and Technology, 74*(3), 339-353.

Weijters, B., Rangarajan, D., Falk, T., & Schillewaert, N. (2007). Determinants and outcomes of customers' use of self-service technology in a retail setting. *Journal of Service Research, 10*(1), 3-21.

Wong, L. W., Tan, G. W. H., Ooi, K. B., & Dwivedi, Y. (2023). The role of institutional and self in the formation of trust in artificial intelligence technologies. *Internet Research*.

Wu, S. I. (2003). The relationship between consumer characteristics and attitude toward online shopping. *Marketing Intelligence & Planning, 21*(1), 37-44.

Wu, W., Rafiq, M., & Chin, T. (2017). Employee well-being and turnover intention: Evidence from a developing country with Muslim culture. *Career Development International, 22*(7), 797-815. https://doi.org/10.1108/CDI-01-2017-0012

Xiong, J., Sun, D., & Wang, Y. (2023). Adoption of artificial intelligence artifacts: A literature review. *Universal Access in the Information Society*, 1-13.

Zavolokina, L., Dolata, M., & Schwabe, G. (2016). FinTech - What's in a name? In *Proceedings of the 37th International Conference on Information Systems (ICIS 2016)*.

Zhou, T. (2012). Understanding users' initial trust in mobile banking: An elaboration likelihood perspective. *Computers in Human Behavior, 28*(4), 1518-1525.

Zhou, T., Lu, Y., & Wang, B. (2010). Integrating TTF and UTAUT to explain mobile banking user adoption. *Computers in Human Behavior, 26*(4), 760-767.

Sadhana Tiwari
GNIOT Institute of Management Studies, Greater Noida- 201310,
Uttar Pradesh,
India
sadhanatiwari.sun@gmail.com
ORCID 0000-0003-3786-3398

Mohammad Asif
College of Administrative and Financial Science Saudi Electronic University
Riyadh 11673
Saudia Arabia
masif@seu.edu.sa
ORCID 0000-0001-6643-6796

Amar Johri
College of Administrative and Financial Science Saudi Electronic University
Riyadh 11673
Saudia Arabia
a.johri@seu.edu.sa
ORCID 0000-0003-2007-8123

Mohammad Wasiq
College of Administrative and Financial Science Saudi Electronic University
Riyadh 11673
Saudia Arabia
m.ahmad@seu.edu.sa
ORCID 0000-0003-0438-039X

Mohd Imran
Assistant Professor of IP Law, Zakir Husain College of Engineering & Technology,
Aligarh Muslim University
India
imrankhan2085@gmail.com
ORCID 0009-0005-6233-2929