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# Global Perspectives on Determinants Influencing the Adoption of AI-Driven Sustainable Fintech Solutions

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## Abstract

Using a mixed methods approach that combines qualitative and quantitative research, this study investigates new developments in artificial intelligence (AI) applications in sustainable Fintech and empirically validates a conceptual research model. It examines important factors impacting the adoption of AI technologies in sustainable Fintech from a cross-national standpoint, highlighting the crucial aspects of advantages, costs, and sustainability characteristics that influence user adoption intentions. To provide a thorough evaluation of scholarly literature on AI, Fintech, and sustainability practices, a bibliometric keyword analysis is carried out using Web of Science and VOSviewer. Sustainability components like transparency and perceived accountability are added to this framework, which has its roots in the Value-Based Adoption Model (VAM) and the Technology Acceptance Model (TAM). The results highlight AI's dual function of promoting sustainable growth and increasing Fintech efficiency. To further the integration of AI in sustainable Fintech management, the study emphasizes the necessity of multidisciplinary cooperation between specialists in sustainability, finance, and AI. This research adds significantly to the body of knowledge in academia and offers useful information to industry professionals and policymakers by linking the domains of artificial intelligence and sustainable Fintech.

**Keywords:** Technology acceptance models, AI tools, bibliometric analysis, sustainable fintech, and cross-national

## Introduction

In the quickly developing financial technology (Fintech) industry, artificial intelligence (AI) has become a key driver of efficiency and innovation. It has significantly improved operational efficiency, accuracy, fairness, and sustainability in the accounting and finance industries. Sustainable finance is a major change in the global finance and investment landscape toward more ethical and sustainable practices by incorporating environmental, social, and governance (ESG) factors into financial decision-making.

The combination of AI and sustainable Fintech has emerged as a crucial topic of study as global attention shifts toward sustainable development. Sustainable finance is becoming more and more important in advancing resilient and responsible economic models by integrating ESG factors into financial services. By facilitating sophisticated ESG risk assessment, increasing transparency, and encouraging accountability, AI accelerates this shift. The financial sector's approach to sustainability is being revolutionized by applications like automated reporting, fraud detection, risk management, and predictive analytics. But there are drawbacks to integrating AI into sustainable Fintech as well, such as complicated regulations, moral dilemmas, and changing norms that stakeholders must deal with.

Risk management, investing, and banking operations have been the main subjects of earlier studies on AI's involvement in sustainable finance. The historical development of sustainable finance has been documented by studies like Gangi's thorough analysis of sustainable investments, which highlights the movement away from conventional tactics and toward sustainability-focused methods. Notwithstanding these developments, there is still a significant knowledge vacuum on user intentions to employ AI tools in the Fintech industry.

In order to close this gap, this study will investigate the elements that influence consumers' acceptance of Fintech goods and services powered by AI. By combining classic elements like perceived usefulness and simplicity of use with crucial characteristics like perceived accountability and transparency, the study expands on the Value-Based Adoption Model (VAM) and the Technology Acceptance Model (TAM). In order to give a thorough grasp of user behavior, the study also looks into aspects of sacrifice, such as perceived dangers, privacy issues, and security difficulties.

The study examines scholarly works on AI applications in sustainable Fintech using text-mining technique to pinpoint important ideas, advantages, and difficulties. The revolutionary effect of AI on sustainable finance is demonstrated through case studies and real-world examples, together with predictions about emerging trends and regulatory issues.

To sum up, this study intends to evaluate AI's present position in sustainable Fintech, investigate user intents around AI adoption, and offer practical insights for business and society development.

The specific research goals are twofold: first, using the Web of Science database, determine current AI trends in sustainable Fintech. Then, using the VAM and TAM conceptual frameworks, examine how perceived benefits and sacrifices affect customers' intents to embrace AI-based products.

## Review of the Fundamental Theories

### AI in fintech

The Fintech industry has grown significantly, combining traditional online banking and payment systems with cutting-edge technology like blockchain and artificial intelligence (AI). Bagó [5] presented the idea of Fintech, highlighting how AI is revolutionizing the financial services sector. He emphasized that the financial technology (Fintech) industry has reached a critical juncture where industry conversations center on the use of artificial intelligence (AI) into financial applications. Likewise, a thorough examination of how AI and data science are propelling innovation in Fintech was presented by Yang and Ding [6]. Their research examines a variety of AI applications in the financial industry, such as automated customer support, fraud detection, algorithmic trading, and credit risk assessment. This report provides insight into future developments in AI-driven financial services in addition to demonstrating the variety of ways AI is being used.

Artificial intelligence (AI) applications in Fintech are transforming fields like fraud detection, high-frequency trading, risk assessment, and customer service automation. AI algorithms can forecast market trends and credit risks by evaluating large datasets, and AI-powered trading systems can optimize investment plans by executing them quickly. Operations have been completely changed by the financial sector's adoption of AI, which has opened up previously unheard-of possibilities for risk management, efficiency, and customisation. These developments are changing the financial landscape and reaffirming AI's position as a fundamental component of contemporary financial services, driven by the rapid progress in AI.
Consumer sentiments about AI-powered robo-advisors were studied by Sabir [7], who found that the Technology Readiness Index, which takes into account elements including perceived convenience, utility, and ease of use, influences favorable opinions. These observations can help financial organizations create robo-advisor services that meet the various needs of their clientele. The suggested paradigm aids in elucidating customer behavioral intentions about the adoption of robo-advisors in the Fintech industry. On the other hand, Flavián [8] discovered that whilst technical optimism increases consumers' inclination to utilize robo-advisors, uncertainty decreases it. Fascinatingly, it was also discovered that robo-advisor adoption was positively impacted by feelings of technological uneasiness. Because AI-driven solutions frequently put users in more passive roles, lowering adoption barriers, these findings defy conventional wisdom on technology uptake. Additionally, the study investigated how consumer knowledge of robo-advisors affects their adoption, providing important information about the variables influencing user interaction with AI-powered financial services.

### Sustainable Fintech

In the financial technology industry, sustainable fintech is a creative and progressive strategy that seeks to advance green finance and match financial services with the sustainable development goals (SDGs). By integrating Environmental, Social, and Governance (ESG) standards into Fintech operations, this integration tackles global issues. Environmental elements (like green finance programs and climate risk assessment), social elements (like ethical investments, sustainable practices, and community involvement), and governance elements (like transparency, accountability, ethical AI, and regulatory compliance) are all included in a thorough examination of sustainable Fintech. These diverse standards guarantee that responsible and comprehensive innovation in financial technology is fostered by sustainable Fintech.
Enhancing financial inclusion by giving underprivileged groups access to financial services is one of the main objectives of sustainable Fintech. For instance, mobile banking allows people to engage in the financial ecosystem even if they do not have access to traditional banking services. In addition to promoting economic expansion, sustainable fintech makes sure that this expansion is fair, inclusive, and environmentally friendly. Fintech companies help achieve the SDGs and establish new standards for the financial sector by integrating ESG principles into their operations.

Ngo, T., Trinh, H. H., and Haouas [9] emphasized the common goals of Fintech and sustainable finance, highlighting how Fintech may advance green finance and improve the sustainability of financial firms. Their study also emphasizes how crucial international and European laws are, especially when it comes to protecting consumers. Similarly, Merello [10] discovered that in addition to conventional economic and financial criteria, sustainability metrics like green certifications and rankings can affect the value of Fintech companies. These results highlight how crucial sustainability is becoming to determining the direction of the Fintech sector.

**AI and Sustainable Fintech Integration**

Due to a rise in scholarly interest in the subject, there have been more publications about sustainable finance in recent years. Only a tiny number of studies have examined the ways in which AI applications and sustainable finance intersect, with the majority of research concentrating on these two areas as separate disciplines. The integration of AI into sustainable Fintech holds great promise for enhancing ESG (Environmental, Social, and Governance) performance, optimizing resource utilization, and advancing the development and efficacy of green financial services and solutions.

Oyewole [11] supports this viewpoint by examining the connection between artificial intelligence (AI) and sustainable development, highlighting the country's efforts to incorporate AI technologies with its Sustainable Development Goals (SDGs). Through better decision-making, resource allocation, and the efficiency of sustainable financial practices, AI can hasten the attainment of these objectives, according to the report. In a similar vein, Vasiliu, Roman, and Prodan [12] describe how AI is promoting advancements in sustainable finance by creating AI-powered financial datasets for green trading and investing. They also explain how AI is used in sustainable

supply chain financing, highlighting how it may increase supply network effectiveness and create business prospects.

The crucial role of AI in sustainable supply chain financing is examined by Olan [13], with a focus on the food and beverage sector. In order to create a sustainable funding ecosystem, this research presents a novel conceptual framework that illustrates how AI may improve supply chain efficiency and transparency. The identification and mitigation of environmental risks, the sustainability of supply chain activities, and the advancement of more general sustainable finance goals all depend heavily on this use of AI.

Additionally, AI has the potential to greatly enhance financial systems' transparency and accountability by monitoring and controlling the social and environmental effects of financial operations. In conclusion, this paper explores the incorporation of AI into sustainable Fintech, considering the technology's vast potential as a catalyst for sustainable Fintech and its increasing significance in the financial sector. The study attempts to offer useful management insights into creating effective, transparent, and responsible financial systems that are in line with international sustainability goals by examining the different ways AI affects sustainable finance.

**Bibliometric Evaluation of Current Academic Research Trends**

Using a mixed-method approach, this study combines quantitative and qualitative data to examine the relationship between AI and sustainable Fintech. The study analyzes collaboration networks between authors and institutions, identifies emerging trends and hot topics in sustainable finance research, and uses VOSviewer to generate keyword co-occurrence network maps based on authors' keywords. Information about the evolution of research topics is provided by keyword co-occurrence network analysis, which highlights popular themes such as "economic growth," "machine learning," "deep learning," "sustainability," "risk management," and "neural networks." These clusters represent connected areas of research and help identify new avenues for sustainable financing. Using a bibliometric search technique with phrases like "sustainable finance," "sustainable Fintech," "AI in Fintech," and "AI in sustainable Fintech," 1,452 papers were found as of June 21, 2024, in the Web of Science Core Collection, which provided the study's data. In order to find trends, monitor collaborations, and pinpoint important figures in the area, bibliometric analysis—which uses mathematical and statistical techniques to scholarly literature—was employed. This analysis maps the relationships between nations, institutions, and authors in addition to revealing the state of development of sustainable finance research.

The study explores the conceptual underpinnings of important subjects like deep learning and machine learning, which employ automation and sophisticated analytics to improve user experience and streamline difficult processes. These technologies are prized for their apparent utility and ease of use, providing Fintech companies with operational efficiencies, tailored advice, and precise forecasts. Another important element is sustainability, which emphasizes moral and responsible behavior. Perceived responsibility and transparency stand out as crucial factors that represent user expectations for accountability in sustainable operations. In order to allay users'

worries about possible losses, risk management is emphasized as being crucial, with security and privacy protocols being crucial in building confidence. Furthermore, neural networks are recognized as essential to the development of AI, facilitating applications like fraud detection, predictive analytics, and personalized investment advice. Additionally, by maximizing resources and encouraging innovation in green financial products, neural networks also support economic growth. The paper also looks at the contributions made by well-known scholars who have pushed the use of AI in finance, including Zeng Zhen, Balch Tucker, and Manuela Veloso. For example, variational autoencoders and LSTM networks are used in Zeng and Tucker's work on "Deep Video Prediction for Time Series Forecasting" to increase the accuracy of financial forecasting. Their study demonstrates how deep learning can improve financial instruments' usability and accessibility while including sustainability concepts like perceived accountability and transparency to meet customer demands for moral behavior. By taking these viewpoints into account, the report emphasizes how AI technology may drive innovation and economic growth while addressing important issues in sustainable Fintech, including risk management, transparency, and privacy concerns. The results provide important information for creating user-centered, responsible, and effective financial systems that support international sustainability objectives. In addition to mapping collaboration networks and identifying important contributors to the field, the study's bibliometric analysis lays the groundwork for future research and useful developments in AI-driven sustainable finance.

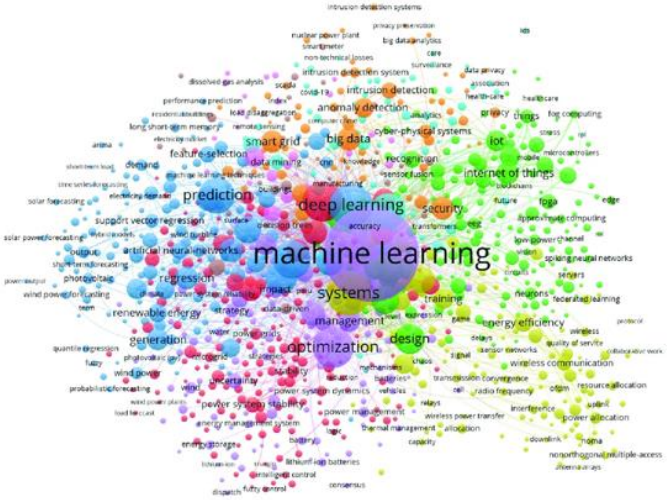


**Figure 1:** Map of keyword co-occurrence analysis

## Development of Research Model and Hypothesis

## Configuration of Research Model

To provide a conceptual framework, this study expands upon two fundamental theoretical models: The Technology Acceptance Model (TAM) and the Value-Based Adoption Model (VAM). With regard to the adoption and use of technology, the VAM is intended to comprehend and forecast human behavior. The VAM provides a more thorough understanding of user behavior than more conventional models like the TAM by expanding the notion of perceived value. To evaluate and

predict user adoption trends, it has been extensively used in a variety of industries, including social networking, mobile technology, e-commerce, and healthcare. The VAM's main objective is to assess the perceived advantages and disadvantages of technology-related goods and services. This model is used by scholars and practitioners to analyze the trade-offs that consumers consider, pinpoint the elements that affect adoption, and create plans to improve user satisfaction and perceived value. The VAM provides a comprehensive method for comprehending the intricacies of user behavior by combining hedonic and social components, in contrast to models that just include utilitarian considerations.

In order to create a strong framework for evaluating the acceptance of AI-based Fintech goods and services, this study will focus on perceived benefits and perceived sacrifices as important adoption criteria. This methodology identifies the key elements that affect user acceptance, offering important insights into how to enhance the overall value proposition, design, and delivery of AI-driven Fintech products.

**Benefits Dimension**

1. **Perceived Responsibility:** The degree to which consumers believe AI-powered Fintech goods and services follow moral and environmentally friendly standards.
2. **Perceived Transparency:** The degree of transparency and clarity with which users are informed about AI-based Fintech operations.
3. **Perceived Ease of Use:** The perception of users that Fintech solutions based on artificial intelligence are easy to use and require little effort.
4. **Perceived Usefulness:** The belief held by users that Fintech solutions based on artificial intelligence improve their overall efficacy and financial decision-making.

**Dimension of Sacrifice**

**Perceived Risk:** The possible negative consequences or unpredictability that users connect with using Fintech solutions that are based on AI.

**Perceived Privacy Concern:** Users' worries regarding the privacy and security of their money and personal data.

**Security Concern:** When utilizing AI-based Fintech products, users worry about the security and integrity of their data and transactions.

**Mediating Variables**

The entire evaluation of the advantages of utilizing AI-based Fintech solutions in comparison to the costs is known as perceived value.

**Adoption attitude:** Consumers' general assessment of utilizing Fintech products with AI.

## The Dependent Variable

Intention to Use AI Tools: How likely it is that consumers will accept Fintech services and products that use artificial intelligence. The adoption of AI-based Fintech solutions is determined by a number of aspects, including perceived benefits and perceived sacrifices. This study offers a thorough framework to comprehend the acceptance of such goods and services. Positive characteristics that promote adoption are highlighted by the benefits dimension, which encompasses perceived responsibility, transparency, ease of use, and utility. On the other hand, the sacrifices component takes into account security, privacy, and perceived risks in order to handle any difficulties. The paradigm attempts to explain the mediating effects of perceived value and adoption attitude, which link these advantages and sacrifices to the intention to employ AI technologies.

Through consideration of ethical, social, and security considerations in addition to the pragmatic aspects of technology adoption, this method provides a more profound understanding of user behavior with respect to AI-based Fintech. This study is especially well-suited to the Technology Acceptance Model (TAM), which offers a systematic framework for comprehending how consumers embrace new technologies with an emphasis on perceived utility and usability. Since consumer perceptions have a big influence on the possibility of adoption, these characteristics are essential for assessing AI-based Fintech solutions. Because of its ease of use and solid empirical support, TAM is a great place to start when looking into the variables affecting the adoption of technology in the Fintech industry. The felt responsibility and perceived transparency dimensions are added to the TAM in this study in order to reflect the distinctive features of AI-based Fintech adoption. Concerns of moral conduct and operational transparency, which are critical in the financial industry, are addressed by this change.

## Justification for the Perceived Responsibility Addition

Customers are assessing technology more critically based on the accountability displayed by the companies that provide it, as they place a greater emphasis on moral and sustainable business practices. Users' opinions on the moral ramifications and Fintech companies' dedication to sustainable practices are reflected in this factor.

In order to investigate how ethical considerations affect users' acceptance and trust in AI-driven financial services, perceived responsibility was included. This entails evaluating the wider societal and environmental effects of the technology as well as the moral conduct of the businesses providing these services.

## Justification for Perceived Transparency

Building user trust now depends heavily on operational and data handling transparency, particularly in AI systems where opaque decision-making is required. Users want to know exactly how AI systems use their data and make choices. Perceived transparency gauges how open and transparent people think AI-based Fintech services operate. This variable was added to evaluate

the relationship between users' desire to use these technologies and operational transparency. It encompasses elements like decision-making procedures, data usage clarity, and the general transparency of the business's operations. This study aims to give a better understanding of the mechanisms and factors driving customer adoption of AI-based Fintech products by including perceived transparency and felt responsibility into the TAM. This enlarged model provides a more thorough and pertinent framework for assessing technology adoption in the financial industry by incorporating traditional technology adoption components with modern concerns about ethics, sustainability, and transparency.

## Research Model

A number of independent variables are divided into benefits and sacrifices in both the extended TAM and VAM models that were employed in this investigation. Perceived usefulness measures how much the technology improves users' performance; perceived ease of use measures how easy it is to use; perceived responsibility measures how users perceive the ethical and sustainable practices in the Fintech industry; and perceived transparency measures how open and transparent the company is in its operations and data management.

However, the sacrifices also include perceived risk, which stands for any unfavorable consequences consumers may connect with the technology. Perceived privacy worry captures users' issues about data privacy, whereas security concern expresses their concerns about the security of data and transactions. Adoption attitude, which indicates users' overall evaluative judgment on the technology, and perceived value, which represents users' overall appraisal of the advantages vs the disadvantages of utilizing the technology, are other model components.

The readiness to use AI tools is the dependent variable, which is the probability that users will accept and employ Fintech goods based on AI. This thorough approach addresses both conventional features of technology acceptability as well as current concerns about ethics and transparency, effectively examining the fundamental factors impacting customer acceptance and uptake of AI-driven Fintech services. Another important component is perceived value, which encompasses the advantages of implementing AI-based Fintech solutions (perceived utility, perceived ease of use, perceived responsibility, and perceived transparency) as well as the disadvantages (perceived risk, perceived privacy concerns, and perceived security difficulties). Customers' overall assessment of whether the advantages outweigh the drawbacks is reflected in it. A high perceived value suggests that people think the technology's benefits outweigh its drawbacks, which raises the possibility that it will be adopted.

Another measure of how consumers feel about using AI-based Fintech goods is their adoption attitude. It depends on how valuable they think the technology is and affects their willingness to use it. Adoption and usage of AI-based Fintech services are more likely when there is a good adoption attitude, which shows a positive opinion of the technology.

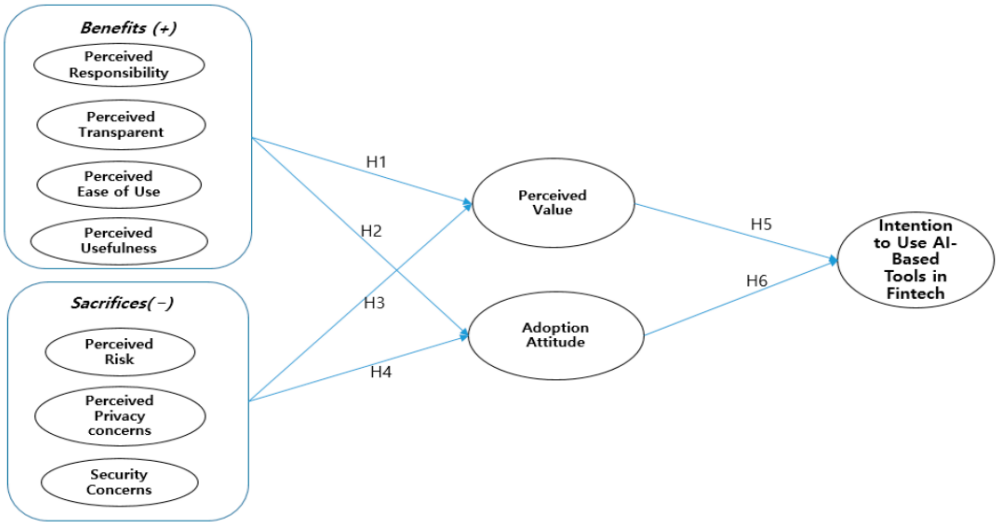


**Figure 2:** Conceptual Research Model

## Development of Hypotheses

The use of AI-based solutions, which have greatly improved accuracy, efficiency, and customization, has revolutionized the Fintech sector. Examining the variables that affect these views is essential to comprehend how suppliers and consumers view the benefits of AI-driven solutions. Important factors including usefulness, accountability, openness, and usability are crucial in assessing how advantageous AI-based solutions are perceived. "Perceived responsibility" describes how consumers feel about the moral, righteous, and socially responsible use of AI-based products. Customers are more inclined to value and trust a product or service if they think it is accountable, according to research. Trust and value are especially important when it comes to Fintech AI-based solutions. Another important element that might raise the perceived value of Fintech technology based on AI is perceived transparency. Similarly, perceived simplicity of use—which includes straightforward procedures and intuitive user interfaces—is essential to enhancing customer satisfaction and raising perceived value. It is anticipated that a major factor in the perceived value of AI-based Fintech solutions would be their perceived usefulness. The degree to which a user thinks a specific system will improve their performance is known as perceived usefulness. Better financial decision-making, time savings, or increased investment returns could all be part of this. In conclusion, recognizing the advantages of AI-based technologies and encouraging their use require an awareness of the elements that influence how suppliers and consumers view them.

The Fintech sector is expected to undergo substantial changes with the advent of AI-based financial services. Understanding user attitudes is crucial for the effective deployment and broad adoption of these technologies. This study emphasizes how users' perceptions of AI-based Fintech solutions are significantly shaped by four fundamental ideas: usefulness, transparency, ease of use, and accountability. Trust and favorable sentiments regarding the adoption of technology are fostered by a sense of accountability. Users are more likely to adopt AI technologies when they

believe there is a high degree of accountability and when they are enthusiastic about using them. Fostering positive adoption attitudes requires high levels of satisfaction and trust, which can be increased by perceived accountability and transparency. Adoption of AI-based Fintech also depends on ease of use, which is a fundamental element of the Technology Acceptance Model (TAM). Positive adoption attitudes are influenced by simple procedures, intuitive user interfaces, and little work needed to get desired results. It is anticipated that adoption attitudes will be greatly increased if AI-based Fintech solutions are seen as being user-friendly. Another crucial component is perceived utility, or how much a user thinks a system will enhance their results. Perceived utility is a key factor in forecasting technology adoption in a variety of scenarios, whether it relates to improving investment returns, saving time, or making wiser financial decisions. The successful implementation and widespread adoption of AI-based Fintech solutions depend on a knowledge of consumer attitudes about these technologies.

Concerns regarding perceived value and possible risks have been raised by the use of AI-based solutions in Fintech and sustainable finance. The term "perceived risk" describes the potential for unfavorable consequences, including problems with performance, moral dilemmas, and financial difficulties, related to the application of AI in sustainable finance. Higher perceived risks are generally associated with poorer perceived value, according to consumer behavior research, particularly when customers are making expensive or time-consuming decisions.

Another important element affecting how valuable AI-based Fintech solutions are seen is privacy issues. Users may be concerned that new technology may appear less useful due to unanticipated or negative financial effects. According to this study, perceived risk will have a detrimental effect on perceived value in AI-driven sustainable finance. Another important consideration is security, which includes safeguarding information and transactions against illegal access and online dangers. Security problems can have a significant impact on users' opinions about a technology's worth and reliability. The financial impact of IT security and the part security perceptions play in fostering user trust and perceived value have been shown in earlier studies, such as those conducted by Cavusoglu and Raghunathan. Adoption attitudes toward AI-powered Fintech solutions are also influenced by perceived dangers, privacy, and security issues. Users may be reluctant to use these technologies because of worries about possible negative consequences or financial instability. Research shows that perceived risk has a detrimental impact on the adoption of new technology in sustainable finance. Consequently, it is anticipated that adoption attitudes will be significantly impacted negatively by perceived risk in AI-driven sustainable finance. This study looks at how people view privacy and security issues in connection to Fintech solutions that use artificial intelligence. Adoption may be hampered by negative views about the usage of AI-based solutions brought on by privacy issues, particularly those pertaining to data breaches or misuse. This relationship is supported by earlier research, which demonstrates that serious privacy issues might result in a poor perception of Fintech products that use artificial intelligence. Users' trust and technological readiness are also impacted by security concerns. According to studies, trust and technological adoption readiness can be strongly impacted by security concerns. Therefore, it is anticipated that adoption attitudes will be adversely affected by perceived security issues regarding AI-based Fintech solutions.

Users' overall assessment of the worth of AI-based solutions is represented by perceived value, which is influenced by elements like usefulness, simplicity of use, accountability, transparency, and other favorable traits. Stronger intents to use a technology are consistently correlated with higher perceived value, according to empirical research on technology adoption. The decision to adopt these technologies is heavily influenced by adoption attitude and preparedness to employ AI-powered tools. Promoting a favorable adoption mindset is crucial for the successful integration and acceptance of AI-based Fintech solutions. According to this study, adopting AI-based solutions is far more likely when one has a positive outlook, which is consistent with research showing that positive attitudes result in increased intents to use technology.

## Data Collection

To create the questionnaire items, we reviewed the literature and carried out exploratory research. We first asked a number of PhD students from a university in the Republic of Korea to pre-screen the questionnaire in order to guarantee the validity and reliability of the suggested measurement scale. We were able to eliminate any questions with unclear or deceptive meanings by using this pre-testing to ascertain whether respondents fully comprehended the items. Graduate students enrolled in Chinese and Korean universities were the target audience for the survey. Following the screening processes we developed; participants were chosen based on their interest in financial technology (Fintech) or their active participation in the Fintech sector. An online survey platform was used to administer the survey between February and March of 2024. We received 465 legitimate responses and after eliminating eight invalid responses. The selection criteria made sure that the sample participants had the required educational background and pertinent work experience, making them suitable to achieve the study's goals.

## Scale Measures

This survey uses a thorough evaluation scale to gauge respondents' opinions about AI technology in the Fintech sector. Each dimension's measurement scales were created after a careful analysis of earlier studies. Responses ranged from 1 ("strongly disagree") to 5 ("strongly agree") for a total of 32 items. Appendix A's Table A1 provides a thorough explanation of the scale's components. The study investigates a number of user impression-related topics.

Perceived responsibility assesses how customers perceive the morality and responsibility of Fintech businesses' usage of AI technologies. It contains claims like "AI-based tools protect users' rights," "AI-based tools meet user needs," and "Accountability in AI-based tools is essential."

Users' perceptions of Fintech businesses' openness regarding their operations, decision-making procedures, and data usage of AI tools are the main emphasis of perceived transparency. Statements such as "AI-based tools clarify the contents and use of personal information collected" and "AI-based tools explain to users the processes and reasons behind their actions" are examples of this dimension. Perceived ease of use scales, such as "I would find it easy to manage investments using AI-based tools" and "learning to use AI-based tools would be easy for me," are used to evaluate the intuitiveness and usability of AI products. By using criteria like "AI-based tools would improve my performance in managing investments" and "I would find AI-based tools useful in

managing investments," perceived usefulness investigates whether users believe AI solutions enhance their productivity, efficiency, and financial decision-making. Perceived risk looks at worries about possible bad things, such losing money, having data compromised, or having AI make bad choices. The following are examples of scales: "I fear that hackers can steal my personal information from service providers' databases" and "I fear that my personal information can be stolen in financial transactions." With metrics like "It would bother me when I am asked for personal data by AI-based tools" and "I am concerned that too much personal data is collected," perceived privacy concerns investigates users' worries regarding the confidentiality of their financial and personal information.

Security concerns employ scales like "I would not feel secure sending sensitive information to AI-based tools applications" and "AI-based tools are not a secure means to send sensitive information" to probe users' worries about the security of their financial transactions and personal data. However, perceived value measures how users feel about the costs and benefits of using AI tools overall. Examples of this include "the use of AI-based tools delivers me good value" and "using AI tools is beneficial to me compared to the fee I need to pay" utilizing measures like "I like the idea of using AI-based tools for managing personal investments" and "using AI-based tools for managing investments seems like a good idea," Adoption attitude measures users' propensity to embrace and incorporate AI technologies into their financial practices. Lastly, the intention to utilize AI tools measure, which includes statements like "I intend to use AI-based tools for managing investments" and "my intention is to use AI-based tools rather than relying on a human financial advisor," evaluates users' propensity to use AI technology in the future. All of these factors combined offer a thorough grasp of how users in the Fintech sector feel about AI products.

## Empirical Analysis

Validity, reliability, demographics, and hypothesis testing are all examined in this empirical study to determine the factors impacting the adoption of AI products in the Fintech sector in India. There were 465 valid responses in a survey that was performed in February and March of 2024. Male respondents were outnumbered by female respondents in both nations, and most participants had Master's degrees and were between the ages of 31 and 40.

Cronbach's Alpha reliability study showed that all constructs in both nations had strong internal consistency, with values over 0.7. The measurement model was validated using both exploratory and confirmatory factor analyses. Kaiser-Meyer-Olkin (KMO) measurements of sample adequacy and significant Bartlett's tests of sphericity, both of which were above 0.97, indicated that the model was appropriate for factor analysis. For both datasets, structural equation modeling (SEM) verified a good model fit.

The results of hypothesis testing showed that perceived value and adoption attitude were significantly positively correlated with perceived responsibility, transparency, utility, and simplicity of use. Adoption attitude and perceived value were adversely affected by perceived risk, privacy issues, and security issues. Remarkably, perceived privacy concerns had no discernible impact on perceived value in Korea. This could be because of cultural reasons, a belief in rules, and a preference for ease and financial gains above privacy concerns.

The intention to utilize AI technologies was highly influenced by perceived value, and in both nations, adoption attitude was found to be a significant predictor of future usage. These results demonstrate how important perceived advantages (like dependability and simplicity of use) and disadvantages (such privacy and security threats) are in influencing how users embrace AI solutions in the Fintech industry.

## Implications and Conclusion

### Theoretical Discussion

With significant theoretical and practical ramifications, this study provides a comprehensive examination of the uptake and customer acceptance of AI solutions in the sustainable Fintech sector. The study reveals important aspects that affect customers' intents to adopt AI-driven financial services by integrating ethical issues with the Value-Based Adoption Model (VAM) and the Technology Acceptance Model (TAM). Although the VAM and TAM frameworks offer insightful information about user perceptions, they have drawbacks and might not account for all the variables influencing behavior. To provide a more thorough knowledge of consumer views of AI-based Fintech, future research should include more theoretical models.

The empirical results show that the way that privacy concerns affect perceived value. The perceived advantages of AI tools are greatly diminished due to privacy concerns, suggesting that Chinese customers place a higher priority on data security and are more circumspect about privacy matters. In Korea, on the other hand, privacy concerns have no effect on perceived value because of cultural norms, faith in the legal system, and a significant emphasis on convenience and innovation. These results highlight how crucial it is to take cultural and contextual aspects into account when researching AI adoption in the Fintech industry.

Practically speaking, the report provides Fintech businesses with doable suggestions. In order to increase the perceived value of AI technologies and encourage user adoption, businesses should place a high priority on developing perceived responsibility through openness, moral behavior, and excellent customer service. Cultural variations in privacy concerns and trust levels should also be included in marketing methods. To foster trust and allay worries, businesses India, for example, can emphasize their adherence to strict data protection laws and their dedication to customer privacy.

Another crucial tactic is to inform consumers of the advantages and dangers of AI systems. Fintech companies may provide webinars, workshops, and other events to educate users about the benefits of AI tools and data security. Users can be further reassured about data security by highlighting certifications and stressing adherence to local privacy regulations. Companies should also aggressively market the effectiveness, practicality, and creative potential of AI products in order to redirect attention from privacy concerns to real advantages. Fintech companies should regularly collect user input and apply recommended changes to solve privacy and security issues. This proactive strategy can improve consumer happiness and trust. By showcasing definite financial

advantages, providing financial incentives like discounts, prizes, or premium features can help promote adoption. Fintech businesses may successfully handle customer concerns and encourage broader industry adoption of AI-driven solutions by combining these tactics.

## Practical Implication

Fintech businesses may greatly increase the perceived value of their AI products, foster user trust, and hasten adoption in a variety of cultural situations by putting these strategies into practice.
More in-depth study on these subjects should be conducted in the future, including cross-cultural assessments, longitudinal investigations, and the incorporation of developing technology. Examining the moral and societal ramifications of AI in Fintech could offer important insights into the elements affecting customer behavior in addition to initiatives to inform and increase user awareness. The study's conclusion highlights the intricate relationships that exist between value-based viewpoints, ethical issues, and consumer acceptance of cutting-edge technology in the quickly changing Fintech sector. Stakeholders may better manage the benefits and difficulties of adopting AI by comprehending and resolving these crucial elements, which will promote long-term financial innovation.

## Limitations and Future Research Directions

This study has a number of limitations, including those pertaining to methodology and data accessibility. The small sample size and scope are two major drawbacks. The sample might not accurately reflect opinions of the general public. The findings may be more broadly applicable if the sample size is increased, and more varied demographic groups are included. Additionally, a significant percentage of respondents were students, and the study only looked at online shoppers who were familiar with AI tools in Fintech, like mobile payment platforms. Another restriction is the absence of participants who are younger than 18. A broader spectrum of participants should be included in future research, especially from the MZ generation, who have more financial resources and are more likely to use Fintech products.

Despite efforts to use big data for analysis, the outcomes might have been affected by restrictions on data availability and quality control. Reliability and accuracy of data are crucial for drawing sound findings. These issues should be addressed in future studies by enhancing data quality and investigating different approaches and data sources. Numerous directions for more research in subsequent studies are presented by this subject. A more thorough grasp of how cultural variations affect the uptake and acceptability of AI technologies in the sustainable Fintech sector might be obtained by broadening the research to include other nations and regions. This would reveal both regional quirks and worldwide patterns. Second, future studies could look into how shifting privacy and data protection laws impact consumer behavior, offering insights into how public policy influences how people view AI technology. Third, researching the joint impacts of AI and other cutting-edge technologies on the Fintech sector, like blockchain, IoT, and quantum computing, may provide a more thorough understanding of how these developments affect consumer acceptance and adoption. Fourth, future research should concentrate on the ethical and

societal implications of AI in Fintech since addressing issues of accountability, transparency, and justice is necessary to win over consumers' trust and acceptance. Lastly, investigating cognitive biases and heuristics using behavioral economics theories may provide important new understandings of the psychological aspects influencing the uptake of AI tools by consumers. Future studies can offer a more comprehensive and nuanced knowledge of the elements driving the Fintech industry's adoption of AI by tackling these areas.

## References

1. Agarwal, R., & Prasad, J. (1998). A conceptual and operational definition of personal innovativeness in the domain of information technology. Information Systems Research, 9(2), 204–215. [CrossRef]
2. Anderson, C. L., & Agarwal, R. (2010). Practicing safe computing: A multimethod empirical examination of home computer user security behavioral intentions. MIS Quarterly, 34(3), 613–643. [CrossRef]
3. Bagó, P. (2023). The potential of artificial intelligence in finance. Economic and Financial English-Language Edition Gazd. Pénzü., 10(1), 20–37. [CrossRef]
4. Bannister, F., & Connolly, R. (2011). The trouble with transparency: A critical review of openness in e-government. Policy Internet, 3(1), 1–30. [CrossRef]
5. Bhattacherjee, A., & Sanford, C. (2006). Influence processes for information technology acceptance: An elaboration likelihood model. MIS Quarterly, 30(4), 805–825. [CrossRef]
6. Cavusoglu, H., Mishra, B., & Raghunathan, S. (2004). The effect of internet security breach announcements on market value. International Journal of Electronic Commerce, 9(1), 70–104. [CrossRef]
7. Chen, Y., & Huang, L. (2022). The role of artificial intelligence in green bonds and sustainable investments: A systematic review. Green Finance, 3(4), 291–307.
8. Davis, F. D. (1989). Technology acceptance model: TAM. In M. N. Al-Suqri & A. S. Al-Aufi (Eds.), Information Seeking Behavior and Technology Adoption (pp. 205–219). IGI Global.
9. Devellis, R. F., & Thorpe, C. T. (2021). Scale Development: Theory and Applications. Sage Publications.
10. Dinev, T., & Hart, P. (2006). An extended privacy calculus model for e-commerce transactions. Information Systems Research, 17(1), 61–80. [CrossRef]
11. Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: A perceived risk facets perspective. International Journal of Human-Computer Studies, 59(4), 451–474. [CrossRef]
12. Fishbein, M., & Ajzen, I. (1977). Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research. Penn State University Press.
13. Flavián, C., Pérez-Rueda, A., Belanche, D., & Casaló, L. V. (2022). Intention to use analytical artificial intelligence (AI) in services–the effect of technology readiness and awareness. Journal of Service Management, 33(2), 293–320.
14. Garg, A., & Kumar, S. (2020). The Relevance of Engel-Blackwell-Miniard Model of Consumer Behavior During Covid-19: A Contemporary Consumer Behavior Survey on FMCG Products In Urban Demography In Uttar Pradesh West.

15. Garg, A., Agarwal, P., & Singh, S. K. A Study of Different Aspects of Consumer Behavior for Online Buying In Delhi NCR For FMCD Products.
16. Garg, A., Garg, V., & Dutta, P. (2016). Impact of Office Ergonomics on Business Performance– (In Special Reference to Noida Region).
17. Singhal, R., & Garg, A. (2015). Study of Online Shopping in Ghaziabad and Noida Region–A Customer Perspective.
18. Gangi, F., D'Angelo, E., Daniele, L. M., & Varrone, N. (2021). The impact of corporate governance on social and environmental engagement: What effect on firm performance in the food industry? British Food Journal, 123(2), 610–626. [CrossRef]
19. Garg, A., Sharma, H., Singh, A. K., Sharma, N., & Aneja, S. (2024). Understanding the unpredictable: Technological revolutions' transformative impact on tourism management and marketing. In *Service Innovations in Tourism: Metaverse, Immersive Technologies, and Digital Twin* (pp. 19–38).
20. Garg, A., Pandey, T. R., Singhal, R. K., Sharma, H., & Singh, A. K. (2024). Exploring enlarged perceptions of value: The utilization of virtual reality in Indian tourism. In *Service Innovations in Tourism: Metaverse, Immersive Technologies, and Digital Twin* (pp. 215–253).
21. Sharma, H., Sahu, N., Singhal, R. K., Tripathi, S., & Singhal, R. (2024). Data-driven forecasting and inventory optimization using machine learning models and methods. In *Proceedings of the 2024 1st International Conference on Advanced Computing and Emerging Technologies (ACET 2024)*.
22. Sharma, H., Garg, A., Singhal, R. K., Sharma, H., & Sharma, N. (2024). Utilizing deep learning and advanced machine learning methods in economic data analysis. In *Proceedings of the 2024 1st International Conference on Advanced Computing and Emerging Technologies (ACET 2024)*.
23. Singhal, H., Singhal, R. K., Garg, A., Sharma, H., & Jaiswal, G. (2024). Analyzing bibliometric systematic reviews on blockchain's role in international e-commerce supply chain management. In *Proceedings of the 2024 1st International Conference on Advanced Computing and Emerging Technologies (ACET 2024)*.
24. Garg, A., Pandey, A., Sharma, N., Jha, P. K., & Singhal, R. K. (2023). An in-depth analysis of the constantly changing world of cyber threats and defenses: Locating the most recent developments. In *Proceedings of the 2023 International Conference on Power Energy, Environment and Intelligent Control (PEEIC 2023)* (pp. 181–186).
25. Kumar Singhal, R., Garg, A., Verma, N., Sharma, H., & Singh, A. K. (2023). Unlocking diverse possibilities: The versatile applications of blockchain technology. In *Proceedings of the 2023 International Conference on Power Energy, Environment and Intelligent Control (PEEIC 2023)* (pp. 187–191).
26. Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. MIS Quarterly, 27(1), 51–90. [CrossRef]
27. Gefen, D., & Pavlou, P. A. (2004). The moderating role of conflict on feedback mechanisms, trust, and risk in electronic marketplaces. Research Note; Management Information Systems Research Center: Cambridge, MA, USA.

28. Gu, J.-C., Lee, S.-C., & Suh, Y.-H. (2009). Determinants of behavioral intention to mobile banking. Expert Systems with Applications, 36(9), 11605–11616. [CrossRef]
29. Juvonen, J., & Weiner, B. (1993). An attributional analysis of students' interactions: The social consequences of perceived responsibility. Educational Psychology Review, 5(4), 325–345. [CrossRef]
30. Kesharwani, A., & Singh Bisht, S. (2012). The impact of trust and perceived risk on internet banking adoption in India: An extension of the technology acceptance model. International Journal of Bank Marketing, 30(4), 303–322. [CrossRef]
31. Kim, D. J., Ferrin, D. L., & Rao, H. R. (2008). A trust-based consumer decision-making model in electronic commerce: The role of trust, perceived risk, and their antecedents. Decision Support Systems, 44(2), 544–564. [CrossRef]
32. Kumar, S., Kumar, P., & Bhasker, B. (2018). Interplay between trust, information privacy concerns and behavioural intention of users on online social networks. Behaviour & Information Technology, 37(7), 622–633. [CrossRef]
33. Liu, Z., Chen, H., & Wang, Y. (2021). Predictive analytics in financial portfolio management using neural networks. International Journal of Financial Studies, 9(3), 45.
34. McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). The impact of initial consumer trust on intentions to transact with a website: A trust-building model. Journal of Strategic Information Systems, 11(3–4), 297–323. [CrossRef]
35. Merello, P., Barbera, A., & de la Poza, E. (2023). Analysing the determinant factors of the sustainability profile of Fintech and Insurtech companies. Journal of Cleaner Production, 421, 138437. [CrossRef]
36. Mitchell, V. W. (1999). Consumer perceived risk: Conceptualisations and models. European Journal of Marketing, 33(1–2), 163–195. [CrossRef]
37. Moore, G. C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. Information Systems Research, 2(3), 192–222. [CrossRef]
38. Mwesiumo, D., Halpern, N., Budd, T., Suau-Sanchez, P., & Bråthen, S. (2021). An exploratory and confirmatory composite analysis of a scale for measuring privacy concerns. Journal of Business Research, 136, 63–75. [CrossRef]
39. Ngo, T., Trinh, H. H., Haouas, I., & Ullah, S. (2022). Examining the bidirectional nexus between financial development and green growth: International evidence through the roles of human capital and education expenditure. Resources Policy, 79, 102964.
40. Ochuba, N. A., Adewunmi, A., & Olutimehin, D. O. (2024). The role of AI in financial market development: Enhancing efficiency and accessibility in emerging economies. Finance and Accounting Research Journal, 6, 421–436. [CrossRef]
41. Olan, F., Spanaki, K., Ahmed, W., & Zhao, G. (2024). Enabling explainable artificial intelligence capabilities in supply chain decision support making. Production Planning & Control, 1–12. [CrossRef]
42. Oyewole, A. T., Adeoye, O. B., Addy, W. A., Okoye, C. C., Ofodile, O. C., & Ugochukwu, C. E. (2024). Promoting sustainability in finance with AI: A review of current practices and future potential. World Journal of Advanced Research and Review, 21, 590–607. [CrossRef]

43. Paulus, M., Jordanow, S., & Millemann, J. A. (2022). Adoption factors of digital services—A systematic literature review. Service Science, 14(4), 318–350. [CrossRef]
44. 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.
45. Regona, M., Yigitcanlar, T., Xia, B., & Li, R. Y. M. (2022). Opportunities and adoption challenges of AI in the construction industry: A PRISMA review. Journal of Open Innovation: Technology, Market, and Complexity, 8(2), 45. [CrossRef]
46. Roca, J. C., García, J. J., & De La Vega, J. J. (2009). The importance of perceived trust, security and privacy in online trading systems. Information Management & Computer Security, 17(2), 96–113. [CrossRef]
47. Rothenberger, L., Fabian, B., & Arunov, E. (2019). Relevance of ethical guidelines for artificial intelligence—a survey and evaluation. In Proceedings of the 27th European Conference on Information Systems (ECIS), Stockholm and Uppsala, Sweden, 8–14 June 2019.
48. Sabir, A. A., Ahmad, I., Ahmad, H., Rafiq, M., Khan, M. A., & Noreen, N. (2023). Consumer acceptance and adoption of AI robo-advisors in Fintech industry. Mathematics, 11, 1311. [CrossRef]
49. Salisbury, W. D., Pearson, R. A., Pearson, A. W., & Miller, D. W. (2001). Perceived security and World Wide Web purchase intention. Industrial Management & Data Systems, 101(4), 165–177. [CrossRef]
50. Schaupp, L. C., & Bélanger, F. (2005). A conjoint analysis of online consumer satisfaction. Journal of Electronic Commerce Research, 6(2), 95.
51. Shin, D. (2021). The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI. International Journal of Human-Computer Studies, 146, 102551. [CrossRef]
52. Snoj, B., Korda, A. P., & Mumel, D. (2004). The relationships among perceived quality, perceived risk and perceived product value. Journal of Product & Brand Management, 13(3), 156–167. [CrossRef]
53. Taylor, S., & Todd, P. A. (1995). Understanding information technology usage: A test of competing models. Information Systems Research, 6(2), 144–176. [CrossRef]
54. Vasiliu, L. A., Roman, D., & Prodan, R. (2023). Extreme and sustainable graph processing for green finance investment and trading. In Proceedings of the 2023 ACM/SPEC International Conference on Performance Engineering, Coimbra, Portugal, 15–19 April 2023 (pp. 249–250).
55. Veloso, M., Balch, T., & Borrajo, D. (2021). Artificial intelligence research in finance: Discussion and examples. Oxford Review of Economic Policy, 37(3), 564–584. [CrossRef]
56. Venkatesh, V., Davis, F. D., & Morris, M. G. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425–478. [CrossRef]
57. Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. Management Science, 46(2), 186–204. [CrossRef]

58. Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. MIS Quarterly, 36(1), 157–178. [CrossRef]
59. Wang, H. Y., & Wang, S. H. (2010). Predicting mobile hotel reservation adoption: Insight from a perceived value standpoint. International Journal of Hospitality Management, 29(4), 598–608. [CrossRef]
60. Yang, P., Ding, Y., Xu, Z., Pu, R., Li, P., Yan, J., & Wang, F. (2020). Epidemiological and clinical features of COVID-19 patients with and without pneumonia in Beijing, China. medRxiv. [CrossRef]
61. Yang, Q., Pang, C., Liu, L., Yen, D., & Tarn, J. (2015). Exploring consumer perceived risk and trust for online payments: An empirical study in China's younger generation. Computers in Human Behavior, 50, 9–24. [CrossRef]
62. Zeng, Z., Balch, T., & Veloso, M. (2021). Deep video prediction for time series forecasting. In Proceedings of the Second ACM International Conference on AI in Finance, Virtual, 3–5 November 2021 (pp. 1–7).
63. Zhang, Q., Li, J., & Xu, S. (2023). AI-driven financial platforms and their impact on SME funding accessibility: Evidence from emerging markets. Sustainable Finance Review, 5, 67–89.
64. Zhang, X., Li, H., Wu, Y., & Li, Y. (2017). Exploring the role of perceived value in the adoption of AI technologies: A study on user experience and satisfaction. Journal of Technology Management & Innovation, 12(3), 34–45. [CrossRef]