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AI Adoption in Islamic Finance using Extended TAM Model with Moderation of Shariah Compliance Perception, Perceived Risk, Perceived Trust.

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ABSTRACT

The unceasing rate of technical advancement that defines the digital era has made a major impact on the direction of the financial industry. One of the fastest-evolving technologies in the world is artificial intelligence. This study examined the relationship between TAM constructs and through an extension of the Technology Acceptance Model (TAM) with perceived risk, perceived trust, and perception of Shariah compliance as moderators, examined the adoption of artificial intelligence (AI) in Islamic banking. We proposed users' Perceived ease of use (PEOU), Awareness towards AI (AWS), and subjective norms (SN) affect perceived usefulness (PU), which in turn affect attitude towards AI (ATT). A positive attitude leads toward behavior intentions (BI) and ultimately continued intention (CI). We also contend that perceived risk of AI (PR), perceived trust in AI (PT), and perception of Shariah compliance (SCP) moderate the effect of PEOU, AWS, SN and PU on ATT, the effect of ATT on BI, and the effect of BI on CI respectively, in a way that higher level of PR, PT, and SCP will make these relationships stronger. This study is carried out as a quantitative, explanatory research technique, statistical data was collected from banking service users through a standardized questionnaire using an online platform in a cross-sectional temporal horizon. The literature is supported by online publications. A total of 350 respondents made up the study's sample size. SmartPLS was used for statistical analysis. The study's empirical findings clarify that all 9 direct hypotheses; perceived ease of use, awareness of AI, subjective norm, and perceived usefulness; all positively impact attitudes, behaviors, and continuance intentions to use AI in the banking industry. The analysis also revealed that all of the 18 moderators' hypotheses from the extension of constructs from the TAM framework, including perceived risk, perceived trust, and Shariah compliance perception, were disproved suggesting that users do not give religious judgment, risk perception, or degree of trust much thought while deciding whether to keep utilizing AI technology in the Islamic banking sector. The conclusions point to the importance of raising acceptability and adoption in Islamic banking by utilizing social influence, raising awareness, and easy-to-use AI solutions. The report provides valuable recommendations to policymakers and practitioners who wish to implement AI technology in a customer-oriented manner, alongside contributing to the growing literature on AI in banking.

Keywords: Perceived Ease of Use (PEOU), Awareness of AI (AW), Subjective Norm (SN), Perceived Usefulness (PU), Attitudes towards AI (ATT), Behaviors Intension (BI), Continuance Intentions (CI), Shariah compliance perception (SCP), Perceived Risk (PR), Perceived Trust(PT), Partial Least Squares Structural Equation Modelling (PLS-SEM).

1. INTRODUCTION

1.1. Background

Both nations with a majority of Muslims and those with non-Muslims have highly well-established and extensive conventional banking. Around the world, consumers are used to and consistently use the traditional banking system for daily transactions. But in recent years, Islamic banking has gained the support and acceptance of all religious communities worldwide because, in addition to the traditional governance structure, Islamic banks also have a layer of governance called shariah governance, which is a crucial tool that they use to reduce the risks of shariah noncompliance (Aspiranti et al., 2023). Islamic banks are financial intermediaries that help link people or businesses with extra money (savers) with people or businesses in need of funding (borrowers) (Jallow, 2023).

The unceasing rate of technical advancement that defines the digital era has made a major impact on the direction of the financial industry. Many consumers are becoming sophisticated and knowledgeable while making purchases. They frequently advocate for less social interaction. In order to reach a larger audience, businesses must discover automation. The use of technology in this area is much more widespread and can improve the financial system's general functioning by providing automation and accurate results (Hamadou et al., 2024).

A rising number of political and economic crises, such as the 2008 financial crisis and the more recent COVID-19 pandemic, have increased the use of digital solutions to address wicked situations (Ashraf, 2023). One of the technologies that is evolving the fastest in the world is artificial intelligence. Its output has expanded due to its application in many other businesses, and the financial sector is no exception. First, let's understand what artificial intelligence is, which is "the capacity to replicate from something that is natural, in terms of learning and using knowledge and abilities." These days, a machine or computer performs this copying function. Thus, artificial intelligence is the ability of a computer to think for itself in a manner similar to that of a person (Latimore, 2018). We must first understand how artificial intelligence functions before we can talk about how it may be used or is beneficial in Islamic finance. The Business Intelligence (BI) System is composed of four main parts: the Data Warehouse, which houses the data's original source; Business Analytics, which includes a collection of tools for altering, mining, and analysing data within the Data Warehouse; Business Performance Management, which tracks and assesses performance; and user interfaces, like dashboards. In addition to powerful analytical skills, BI systems are beginning to incorporate artificial intelligence capabilities. A branch of computer science called artificial intelligence uses symbolic reasoning to solve problems. According to Maryadi et al. (2024), artificial intelligence and machine learning are cognitive organizations that use both organized and unstructured data together with incredibly sophisticated analytical approaches to find, evaluate, and recommend commercial operations.

The use of AI in many fields has mainly attracted interest from around the globe since the beginning of the global financial crisis in 2008 and the most recent COVID-19 pandemic. After the financial crisis, innovation in the banking industry started to be applied to the products that generated the most revenue for the banks. In an effort to recover from the financial crisis, banks have begun to develop new products that bring in enormous sums of money. The use of AI

technology to automate financial transactions is one of these advances that has gained widespread use (Hamadou et al., 2024). Artificial intelligence is being adopted by the banking sector for a number of reasons. Artificial intelligence is the future of the banking sector because of its capacity to employ advanced data analytics to stop fraudulent transactions and improve compliance. AI will increase human productivity and make it possible for people to perform calculations that would be difficult to perform by hand much more quickly and easily, even while it won't replace humans. Artificial intelligence also helps the banking sector lower risk and increase revenues by improving customer satisfaction. All banks must integrate artificial intelligence into their present plans due to the fierce competition and quick speed of innovation in the financial sector (Kochhar et al., 2019). As a result, the banking sector is going through a digital transformation that will have a big impact. Efficacy benefits have increased for banks that use digital banking services. One of the major area where the financial institutions have made a noteworthy investment is Artificial intelligent and automation (Hamadou et al., 2024).

There are several benefits of using AI in Islamic banking, or businesses that operate under Sharia law; those advantages are improving the supply of financial and social facilities, increasing the usefulness and productivity of monetary tasks and facilitating improves risk management. By encouraging assetbacked lending, which requires that transactions be linked to physical assets, Islamic finance helps to curb speculative activity. Islamic financing institutions mainly focus on enabling justice and equity in their monetary tasks. The main difference between Islamic and conventional bank is that Islamic bank only follow equall profit and equall loss sharing method unlike other banks who work on loans provided based on interest; because of this the demand for Islamic financing has grown rapidly as users believe in shariah compliance principles (Iqbal and others, 2025). Additionally, data from earlier research indicates that Islamic banks promote financial and economic stability because of their improved risk management procedures, more sophisticated human resources, and well-established regulatory frameworks (Charag et al., 2020).

The features of AI that it decreases the need for human workforce, providing better check in balance of financial statement and providing automatic monitoring service; improves the accountability. Another feature of AI that helps in making improved risk management and policy making decision in Islamic finance is envisage analytics capabilities. Furthermore, AI systems can now analyze enormous volumes of fatwas in Islam related to finance, indentures and authorized document; all thanks to natural language processing, which organize all of these into clear rules requirements and decrease the chance of human error in making decisions for financing. AI can also detect deceiving practices if any happen in financing by using algorithms in its real time cheat uncovering feature; through this it instantly catches suspicious activity happened and mark with flag and all of this work is done under the rules followed by the shariah. It also identifies financial malfeasance and fraud. Likewise, to this, Chatbots powered by AI used in Islamic banks and computer-generated responses help customers make Sharia-compliant investment selections and make sure their financial decisions are in line with Islamic moral principles. Additionally, by reducing human error and enhancing contract transparency, AI feature that maintain list of all data base gurantee adherence to Islamic rules (Shalhoob & Babiker, 2025).

This study used Technology Acceptance Model (TAM) framework first developed by Davis (1989). The original model has two main constructs that are perceived ease of use and Perceived usefulness; while the model is also open for more external variables; this Ikhsan et al. (2025)

extended this model by adding more variables to investigate perceived risk, perceived trust, subjective norms, and AI awareness. Their study proved the importance of all these variables to be considered while designing the customers based AI services especially to be used in Islamic banking. They revealed the importance of these added variables to be measured if we want to know how the customers feel related to the adoption and knowledge of new technologies and their intention to use them in future as well. However, their study has some research gaps and limitations which they highlighted by mentioning the need for more research.

1.2. Problem Statement

Although the use of Artificial intelligence in Islamic business presents lawful and ethical challenges because all must be followed according to the principals of Islamic rules, consisted of transparency, impartiality, and the restricting of all transactions based on interest and speculation, the integration of this technology into Muslims' daily lives is nevertheless noted. The use of AI may be made extremely difficult by the requirement to uphold Sharia compliance, which includes the prohibitions against using interest (Riba), excessive uncertainty (Gharar), interdiction of gambling (Maysir), and investment of unprincipled things in any of the institution's operations (Shalhoob & Babiker, 2025). However, there are significant ethical issues with the combination of Sharia compliance and AI, including algorithmic choices, AI biases, transparency, and—above all—trust.

From the standpoint of the client, adopting it entails significant risks and drawbacks. One of these concerns is the loss of their personal information captured by AI such as financial transaction history or biometric data which can be used for other purposes or by unauthorized parties without their consent, having no visibility or control over how AI is used by Islamic banks and how their data is processed, concern regarding discrimination that AI might reinforce related to factors such as gender, race or religion, which may affect customers' access to financial products and services (Norrahan & Badruddin, 2023), the inability to understand AI due to low level of readiness for the use new technology in Islamic banks as some of its services are quite easy for customers to use, while others still require adjustments and further development, difficulty in using the services due to operational complexity, concern regarding a technical failure which could hinder the use of the AI Islamic banking services, loss of human based customer support as it's an artificial robotic process acting on behalf of human which may make them lose personal connection with Islamic banks and this may not generate a good and responsive user experience.

AI's widespread application in society is still in its infancy. This is partially because to a lack of technical expertise inside the organisation and the expenses of implementing the necessary technology, which affect the readiness to accept that technology (Chukwuani & Egiyi, 2020). The most difficult aspect of using AI is integrating current systems and business procedures.

1.3 Gap Analysis

Abdullah and Almaqtari, (2024) research investigated how can AI tools such as big data analytics, cloud computing and deep learning could be useful in improving accounting and auditing practices in Saudia Arabia. Rahman et al., (2023) studies on FinTech for Malaysian banking services found out that despite of all its opportunities there still was a threat to the banks which should be researched further Liu and Luo (2022) study on adoption of Youtube as a supplementary tool. Kashive et al., (2020) research on AI enabled e-learning shows high enrollment but low completion rate Singh et al., (2020) study carried out with the intention to find-out the behavioral patterns of the Indian users on adopting mobile wallet as an alternate mode of payment service and

Ikhsan et al. (2025) conducted a study on the use of AI in the banking industry of Indonesia to investigate perceived risk, perceived trust, subjective norms, and AI awareness as TAM extensions. All the hypothesis was solved and found to be true but many variables showed weak relation between constructs.

Past studies grounded on Islamic bank services consider their customers satisfaction driver and desire and intention of continuously using their services based on religiosity (e.g., Suhartanto et al., 2018; Suhartanto, 2020; Muslim et al., 2013; Suhartanto et al., 2022), directing human deeds (Ezeh & Nkamnebe, 2019), as Islamic banks main goal is to satisfy the demands of their customers in accordance with the Islamic rules

These studies didn't account for perceived ease of use, perceived usefulness, and behavioral intention of users in adapting new technology, considering limitation of time as AI is a technology which changes or updated over time, they also only focused on adoption of the technology and missed the side where obstacles arise in its implementation future research should be done on addressing the challenges face by the organizations in AI adoption. Moreover, none of the study examined all of these variables in a unified model and their influence on consumers' decision to continue using AI in Islamic banks.

This study presents a complete model of factors essential to examined while adopting AI in banking sector by re-arranging the base paper variables and incorporating additional moderating variable of risk, trust and another variable relevant to Muslim cultural setting, namely, Shariah Compliance Perception into the framework of TAM to understand customer attitudes and their intention to continue implementing AI in Islamic banking.

1.4 Research Question

1. How do users Awareness, perceived ease of Use and Subjective Norm directly affect the Perceived usefulness of the AI technology in Islamic banking sector?
2. How does user's perception AI's usefulness shape their Attitude towards adopting AI technology in Islamic banking sector?
3. How does users Attitude towards AI directly influence their Behavioral Intension to use that technology in Islamic banking sector?

4. How does the Behavioral Intension to use AI technology impact user willingness to continue its use in Islamic banking?
5. In what way do Shariah Compliance Perception and Perceived Trust positively mediate relationship between different TAM variables (PEOU, AWS, SN, PU, ATT, BI) and Continuance Intension?
6. How do Perceived risk negatively mediate the relationship between different TAM variables (PEOU, AWS, SN, PU, ATT, BI) and Continuance Intension?

1.5 Research Objectives

In the current study our main objective to the find the direct and indirect impact of constructs and their moderators on the continuance usage of AI technology in the Islamic banking sector. This is a multifaceted study that focus on relationship between TAM constructs and through an extension of the Technology Acceptance Model (TAM) with perceived risk, perceived trust, and perception of Shariah compliance as moderators, examined the adoption of artificial intelligence (AI) in Islamic banking. The research aims to find the direct impact of Perceived ease of use (PEOU), Awareness towards AI (AWS), and subjective norms (SN) on Perceived usefulness (PU) and Attitude towards AI (ATT). It seeks to find how positive impact of these variables on Perceived usefulness (PU) influence the positive Attitude towards the AI (ATT) usage and how a positive attitude then leads toward Behavior intentions (BI) and ultimately Continued intention (CI). Furthermore, this research will also explore the positive moderating impact of Perceived trust in AI (PT), and perception of Shariah compliance (SCP) and a negative moderating effect of Perceived Risk of AI (PR) of Perceived ease of use (PEOU), Awareness towards AI (AWS), subjective norms (SN) and Perceived usefulness (PU) on Attitude towards the AI (ATT), the effect of ATT on Behavior intentions BI, and the effect of BI on Continuance intention (CI) respectively, in a way that higher level of PR, PT, and SCP will make these relationships stronger.

1.6 Significance

In light of the changing Islamic financial landscape, this research is important with regard to the strategic application of artificial intelligence. The study gives researchers, financial institutions, and policymakers a better understanding of people's willingness to embrace AI-enabled banking solutions that are consistent with their ethical and religious convictions by providing thorough insights into customer perceptions and their intentions to stick with the service. It helps Islamic banks pinpoint the main factors that influence AI adoption and clarifies how AI may be used to improve customer approval, service quality, and trust while maintaining Shariah compliance. Additionally, this study helps Islamic bank managers create creative plans for integrating AI successfully, which enhances operational effectiveness, risk assessment, regulatory compliance, and client interaction. It also offers important insights into how AI technologies might ethically affect consumer behaviour in line with Islamic principles when seen through the prism of Islamic consumption behaviour. This study opens the door for revolutionary advancements in Islamic banking by identifying and promoting Shariah-compliant AI solutions. Additionally, it offers

practical recommendations for optimising the use of AI, which will eventually aid in the modernisation and long-term expansion of the Islamic financial industry.

2. LITERATURE REVIEW

2.1. Islamic Banking and Finance

Both nations with a majority of Muslims and those without a majority of Muslims have highly well-established and extensive conventional banking. Customers all throughout the world are used to the traditional banking system and consistently use it for routine transactions. Nonetheless, in recent years, Islamic finance has gained broad support and acceptability from all religious communities worldwide (Charag, 2020).

Islamic banks are financial intermediaries, connecting individuals or businesses that have surplus funds with those who require financing (Jallow, 2023). Unlike conventional banks, Islamic banks operate in accordance with the principles of Islamic Shariah, which are rooted in the teachings of the Quran, the traditions of the Prophet (Sunnah), and Islamic jurisprudence (fiqh) (Hamadou, 2024). Based on the principles of Islamic sharia'a (Islamic law), Islamic banking forbids not only any kind of predetermined rate of return or interest but also investments in sectors deemed haram (prohibited), including alcohol, tobacco, pork products, gambling with money and non-money assets (maysir), speculation, pornography, and more. It functions on a profit-and-loss sharing basis and offers an unpredictable rate of return as an alternative to banking (Charag, 2020).

Moreover, traditional banks, driven primarily by profit, often impose high interest rates on loans. This practice can place a heavy burden on borrowers, particularly those from low-income backgrounds, making it difficult for them to access financial support. In response to these concerns, Muslim scholars and leaders around the world began advocating for an alternative banking model that eliminates interest-based transactions. One of the early efforts in this direction emerged in Pakistan as early as the 1940s, marking the beginning of the movement toward interest-free, Shariah-compliant banking.

Furthermore, encouraging the construction of Islamic banks is a key function by Organisation of Islamic Cooperation (OIC). The group hosts conferences to talk about topics that impact its members, such as economic activity and potential remedies. The organisation thus talks on establishing Shariah-compliant institutions that forbid transaction based on interest and encourage profit-sharing (Hamadou, 2024).

2.2. About AI

Robotic process automation, machine learning, and other technologies with human-like skills are all included under the general category of artificial intelligence. Artificial intelligence encompasses several subfields with varying focusses based on their historical and technical

origins. According to this study, AI is the capacity to educate computers to accomplish jobs that humans can now perform better. Machine learning, which is the capacity of systems or applications to learn without any explicit programming, is progressively replacing the human trait of adaptability to settings and behaviors (Thowfeek, 2020).

2.3. AI Adoption in Islamic Banking Industry

One fundamental social component that assesses the operational sufficiency of other global sectors is the banking industry. Although this sector is among the most well-established in the world, it also faces many difficulties, including security, risk management, and inefficiencies that lower an organization's overall performance, as well as the difficulty of updating equipment and training human resources, which usually places a heavy financial burden on these organizations. According to actual evidence from previous studies, artificial intelligence is a promising solution since it improves financial sector functioning and efficiency (Almutairi and Nobanee, 2020).

Patel et al. (2022) highlight that artificial intelligence (AI) offers faster and more efficient solutions compared to traditional methods for performing various financial computing tasks within banking operations. In addition, the core capabilities of AI combined with the increasingly competitive nature of the banking industry make its integration into banking processes not only beneficial but virtually inevitable.

Financial institutions are increasingly using AI and machine learning in a number of financial system applications, including credit quality evaluation, insurance contract pricing and marketing, and customer service automation (Board, F.S. 2017). AI technology, including voice recognition and predictive analytics, is presently being used by financial service providers to assist banks compete with FinTech firms and get the benefits of digitalization (Ortiz Berger, 2022). Because they manage credit, currency, and financial transactions, banks are regarded as the lifeblood of an economy. Given that the financial system is so interconnected, it is possible to trace every transaction and share information from anywhere in the globe by just connecting to these networks. The employment of artificial intelligence by banks is the only reason why the banking industry runs smoothly through computers and networks. To remain relevant in a complicated and competitive industry, banks must continuously change the way they operate. The secret to doing this is to keep customers loyal, which entails taking care of their perceived worth, dedication, trust, and contentment.

Even while AI is being employed in the banking business, the technology is still in its infancy. Due to multiple barriers to adoption, only around 10% of organisations employ AI to compete in the market (Frankel, 2018). This is because using AI in critical infrastructures, like the banking sector, presents a number of hurdles because of their unpredictability. The majority of these concerns center on matters of security, accuracy, safety, and reliability. Considering the risk, banks has adopted cutting-edge technologies such as chatbots and artificial intelligence to increase customer satisfaction (Vedapradha and Hariharan, 2018).

The services segment based on Islamic rules is expanding, and artificial intelligence (AI) has several uses in this field. Advancement in financial services improves the effectiveness, responsiveness, transparency, and cost beneficial monetary services for Islamic clientele (Ali et al., 2019).

AI enables the financing institutions to use cutting-edge analytical tools and innovative business solutions, enabling banks to provide multichannel customer access, learn about customer preferences, and customize services to meet the demands of their clients (Shmuratko and Sheludko, 2019). Big data analysis and artificial intelligence (AI) enable financial institutions to make more educated and data-supported choices about credit management, which lowers credit risks, minimizes losses, and boosts profitability (Alzeaiden, 2019).

The financial service industries, where customer and transaction data is the primary resource that is continuously gathered, sorted, processed, and connected, demonstrate the promise of artificial intelligence (Thowfeek, 2020). In order to generate precise forecasts of possible investment opportunities in the financial markets and to reduce potential risks brought on by the current market conditions, artificial intelligence (AI) systems can analyses market trends in real-time using both structured and unstructured data (Mishra et al., 2017).

Over the past ten years, financial technology, or FinTech, has transformed the finance sector by raising user value and business profits. Robo-advisors, which automate or help manage investments by substituting human advisory services and/or the customer's own management, are a new breakthrough in the finance business, according to study by Flavián et al. (2022) on AI-based financial services. These cutting-edge services, which differ from the majority of mechanically based automation (such as robots), are founded on analytical AI, or the ability to interpret and learn from data in order to solve problems.

Chatbots are powerful artificial intelligence (AI) tools that effectively manage front-office tasks including multilingual customer interactions, lightning-fast response times, and accuracy improvement.

On behalf of banks, chatbots can manage engaging and intriguing communications with many customers in several languages, which may save money and improve customer satisfaction (Khan & Rabbani, 2020). Suhartanto et al. (2022) in their study found out mobile banking based on AI technology increased the loyalty of Islamic bank clients. Based on their gathered information they found that mobile banking with AI capabilities enhances customer satisfaction and service quality. They also proposed that Islamic mobile banking based on AI provide the benefit of boosting operational competence for Islamic banks and help them offer their customers better customer service.

2.4. Theoretical foundation and hypothesis development

2.4.1. Continuance Intension (CI)

A behavioural construct known as "continuance intention" (CI) refers to a person's decision to continue using a specific technology or service based on previous usage experience and expectations about the technology's usefulness, satisfaction, or advantages (Bhattacharjee, 2001).

Liao et al. (2009) initially created the technology continuity hypothesis to determine whether or not people plan to keep utilizing a technology. This theory predicts long-term usage behavior for new technologies by integrating three information system models: the cognitive model, expectation confirmation theory (ECT), and the Technology Acceptance Model (TAM) (Liao et al., 2009).

Based mostly on expectation-confirmation theory (ECT), Bhattacharjee (2001) suggested a postadoption model that explains continuing usage of information systems in order to increase the efficiency of a current technology and produce new technologies that are extensions of the original. Oliver (1980) defined the process by which customers arrive at repurchase intentions using an ECT framework as follows: Before purchasing a product or service, people have an initial anticipation of it. Secondly, they embrace and make use of that good or service. They develop opinions regarding its performance after a time of initial intake. Third, they evaluate how well it performs in comparison to their initial expectations and ascertain how much of their expectations are met. Fourth, their amount of confirmation and the anticipation that led to that confirmation determine their level of contentment, or affect. Lastly, happy customers decide to buy it again, but unhappy customers stop using it after that.

Oliver (1980) proposed a basic cognitive model for satisfaction decisions. According to this concept, attitude is preceded by pleasure, which is a function of expectations and disconfirmation. Additionally, it is clearly acknowledged that a product or service's long-term sustainability and eventual success depend on several usage phases rather than just initial approval.

According to Bergmann et al. (2023), researchers typically use the Theory of Planned Behavior and the Technology Adoption Model to investigate the factors that impact consumers' adoption of certain technologies during the early stages of deployment. However, because consumer decisions are the same as those to continue using a certain technology, it is critical to consider how technology is utilized sustainably. This is due to the fact that both choices include preliminary choices (adoption and technological experience), which results in early decision-making. Customers' desire to employ AI technology in the future was measured in this study as their intention to keep using it. If people do not embrace or gain from a technology, it will fail (Bhattacharjee & Lin, 2015).

2.4.2. Technology acceptance model

Numerous academics have examined how people embrace new technology, and various theoretical models have been developed to characterize and anticipate user behavior for both general and specialized technologies.

The TAM has been frequently used by researchers to assess how customers perceive technology. The TAM was created for the IS discipline in the late 1980s (Davis, 1985 and Davis et al., 1989). Its foundation was the theory of reasoned action (TRA), an intention theory that contends that attitudes and subjective standards shape intention, which in turn shapes actual behaviour (Fishbein & Ajzen, 1977).

According to TAM, the internal variables are motivated by two external factors related to system design characteristics: perceived usefulness (PU) and perceived ease of use (PEOU). PEOU refers for " how much the user perceive the system is easy to use," whereas PU denotes "the user's perception related to how useful this system will be for them". PEOU has a direct correlation with PU and attitude (Davis et al., 1989). However, the TAM appears to be restricted in its capacity to capture consumers' attitudes and behavioural intentions towards technology adoption because it does not include economic, demographic, or external elements. As a result, by adding new components, many technology adoption studies expand upon or enhance the original TAM. As drivers of perceived usefulness and perceived ease of use, TAM actually allows for the addition of external factors (Davis, 1989). TAM also makes the assumption that prospective customers have unrestricted freedom to act and make their own decisions. Consumers may really impose limitations on their freedom of action, such as the rationalisation of traditional banking channels, which is why many of them have tended to embrace new technologies in recent years (Nguyen and Dao, 2024).

The "Technology Acceptance Model" (TAM) is based on the "Theory of Reasoned Action model" (TRA), which incorporates behavioural goals, attitudes, and external factors to comprehend individual internal ideas and attitudes. Two internal psychological factors that directly influence user behaviour are attitude and behavioural intention. According to Davis et al. (1989), attitude is defined as "the feeling of the user either positive or negative about doing a specific task." A new technology may elicit favourable or negative attitudes depending on how beneficial and simple it is seen to be. According to Ajzen (1991), behavioural intention is a gauge of how strongly someone is prepared to attempt and strain themselves when engaging in a certain behaviour. Users' attitudes towards technology and their perceptions of its utility influence their behavioural intention.

For at least three reasons, IS researchers gave TAM a lot of attention. First, psychological theory provides a solid basis for it (Chau, 1996; Taylor and Todd, 1995). Secondly, it is economical and may serve as a model for creating an effective information system. Third, the model is resilient across time, setting, people, and technology, according to a previous line of study (Venkatesh & Davis, 2000).

Additionally, information systems have made extensive use of the Technology Acceptance Model (TAM) to describe user intents to accept and employ new technologies (Al-Adwan et al., 2023).

2.4.3. Perceived ease of Use (PEOU)

According to Rogers (1995), customers who understand technology are more inclined to accept new services or goods. In his research, he established that perceived ease of use relates to how simple an innovation appears to be to understand, learn, or use. He added that perceived ease of use refers to how buyers perceive a new product or service to be easier to use than its competitors.

Perceived ease of use refers to users' belief that technology is simple to use, and it impacts the adoption of new services or items (Davis et al., 1989). Masoud and AbuTaqi (2017) define perceived ease of use as the degree to which innovations are easy to understand, grasp, and implement. However, even if potential users believe a certain application is beneficial, they may believe that the system is too complex to run and that the effort necessary to utilize it outweighs the performance benefits (Davis, 1989).

Customers' reactions to technology can therefore influence whether they are willing to utilize it or not. Negative attitudes towards technology might result from worries about how difficult it is to embrace. Customers who employ technology, on the other hand, readily produce positive and helpful attitudes. One of the most crucial aspects affecting consumers' decision to utilise or not is how easy it is to obtain the information offered (Malaquias & Hwang, 2019).

Research has shown that user attitudes and the perceived value of AI in financial auditing (Damerji & Salimi, 2021) and Internet banking (Rahi et al., 2021) are positively impacted by perceived ease of use.

Perceived ease of use tends to "wear out" over time as users get more accustomed to using IT, according to research on IT continuation (Karahanna et al, 1999; Bhattacharjee, 2001). According to the reasoning, IT that is perceived as being extremely challenging to use is less likely to be adopted by cautious consumers since first-time users must overcome major learning obstacles. High learning barriers, however, do not limit further use after that barrier has been removed.

Developing technologies that are accessible, responsive, and flexible is the driving force behind the emphasis on usability. Humans are more inclined to accept technology that fits these conditions. According to Nadeem et al. (2021), the goal is to satisfy customer demands without overburdening them with needless complexity. According to Wibasuri (2022), customers tend to choose effective solutions that streamline operations, even when oversimplification may occasionally discourage utilisation.

According to the results of other studies, this one makes the assumption that a banking sector that makes investments in easily comprehensible AI-based technology would have a favourable effect on the sustainability of the bank and attract devoted clients. Thus, the following hypothesis was put out in this study:

H1: Perceived ease of use positively influences the perceived usefulness of using AI.

H4: Perceived ease of use positively influences user's attitude toward AI.

2.4.4. Awareness towards AI (AWS)

Awareness is the result of a company's communication strategy for informing customers about the benefits and applications of certain technology. A crucial aspect in the acceptance and adoption of new technology is awareness. Customers who are unaware of a system get concerned and are reluctant to embrace the new technology. Consumers who are worried about data loss, third-party control over personal data, and third-party abuse of data will constantly want to utilise technology as little as possible, which will impact technology acceptance. This suggests that consumers' opinions on how beneficial technology is rely on their awareness level (Singh & Sinha, 2020).

Awareness is the sum of a person's understanding of its benefits, possible disadvantages, and useful applications. Research on technology use has demonstrated a significant correlation between awareness levels and attitudes towards new technologies (Shahzad and colleagues, 2024). Customers who learn about robo-advisors on their own or directly from their banks are more likely to use the service, demonstrating the significant impact of awareness in shaping user perceptions of the technology's utility for banking services and their positive attitude towards increased acceptance of that technology (Flavián et al., 2022). This suggests that customer knowledge has a favorable impact on the intention to utilize new technologies. The following hypothesis was proposed in this study based on the factual evidence described above:

H2: Awareness of AI positively affects perceived usefulness.

H5: Awareness of AI positively influences user's attitude toward AI.

2.4.5. Subjective Norm (SN)

One's intentions towards a certain behaviour are shaped by normative influences from peers or referent people, such as friends, peers, or coworkers. The subjective norm construct, which is the amount to which people believe that a major individual or group of people would approve and support a given conduct, is used to reflect these normative effects (Fishbein & Ajzen, 1975). Furthermore, subjective norms and social influence—that is, the views and influence of others—are synonymous (Taylor & Todd, 1995). Subjective norms in this study refer to the opinions and encouragement of people in the vicinity of consumers who advocate for the use of AI in banking. One important social element that motivates users to do particular activities is the subjective norm. It is defined as the perceived external demands (from significant others, for example) on whether to take a particular action in a particular circumstance. Their perceived value based on interaction will serve as a standard for subsequent users who could choose to engage as a consequence of others' experiences, according to users with prior consuming experiences, such as creative or self-capable users (Lee and Kim, 2021).

Previous researchers who have used AI have shown that subjective standards have a favourable influence on consumers' motivation to continue using technology by providing suggestions. Attitude towards AI, perceived utility, and subjective norms all have a substantial impact on intention to employ AI in financial services (Rahman et al., 2023). According to Abubakar and

Ahmad (2014), bank clients were more willing to utilise AI if they received more feedback from friends, family, and other people. When choosing to adopt new technology, other people's recommendations are beneficial since social influence is more powerful when there is no past experience with the technology (Mer & Viridi, 2023).

Customers' attitudes towards utilising technology based on suggestions are positively impacted by subjective norms. Customers of banks were more willing to utilise AI if they got more feedback from friends, family, and other people. Thus, the following hypothesis was put out in this study:

H3: Subjective Norm of AI positively affects perceived usefulness.

H6: Subjective Norm of AI positively influences user's attitude toward AI.

2.4.6. Perceived usefulness (PU)

People frequently utilise or do not use an application based on how much they believe it will enhance their ability to perform their tasks. Perceived usefulness is defined as "the degree to which a person believes that using a particular system would enhance his or her performance." F. D. Davis (1989). According to this survey, bank clients who think that utilising AI would be beneficial and enhance transaction performance rapidly and with little effort are expressing conceptual perceived utility.

Because these attributes are typically correlated with the tool's utility, consumers tend to favour apps that are knowledgeable, skilful, and easy to use. Customers' perception that adopting a new technology would improve their performance is reflected in usefulness (Shahzad et al., 2024). Perceived utility has a lasting impact on users' information technology use since they are reluctant to stick with new technology unless it helps them in their future job, according to empirical studies on IT adoption and continuation (Bhattacharjee, 2001). Customers of banks are encouraged to have a good attitude towards technology because they see the advantages of adopting AI features to facilitate seamless transactions (Rahman et al., 2023).

According to this study, AI can help consumers in the banking industry by facilitating all transactions. Consequently, favourable attitudes are developed. The following hypothesis was put out in this study based on the results of earlier research:

H7: Perceived usefulness positively influences user's attitudes toward AI.

2.4.7. Attitude towards AI (ATT)

Fishbein and Ajzen (1975) define attitude as the "learnt predisposition to respond in a consistently positive or negative manner with respect to a given object." It is one of the primary aspects

influencing how customers react in real life. As a result, the mentality of bank customers is critical to the success of any effort to promote Islamic banking (Charag et al. 2020).

According to a cited study (Nguyen & Dao, 2024), the primary determinants of consumers' adoption of technology-based financial services seem to be their attitudes and intents. In the context of the services environment, attitude is a good indicator of people's intentions. Regarding Islamic consumer behaviour, it has been discovered that a user's attitude directly influences the development of positive behaviour when utilising AI-based robots (Roy et al., 2022), Internet banking (Rahi et al., 2021), mobile payments (Mobarak et al., 2024), and the adoption of online trading (Yang, 2010). Based on empirical research findings, this paper assumes that integrating AI into the banking business would result in positive alterations in customer perceptions, which will stimulate positive behavioral changes towards AI adoption. Thus, the following theory was presented in this study:

H8: Attitude toward AI positively influences behavioral intention to use AI.

2.4.8. Behavioral Intension (BI)

Individual behaviour is based on reasoned and planned action that results from and is consistent with people's conscious intentions about that behaviour, according to social psychology research such as the theory of reasoned action (TRA) (Fishbein & Ajzen, 1975) and the theory of planned behaviour (TPB) (Ajzen, 1991). This type of rational behaviour also serves as the foundation for IT acceptance models such as TAM.

According to the original TAM model (Davis, 1985), customer attitudes following technology use result in behavioural intention. Numerous studies have found that a wide range of variables impact behavioural intention. Technology accessibility, knowledge of its benefits and applications, and firsthand experience with its use allow users to develop stable behaviour intentions for future use (Singh et al., 2020). According to this study, bank customers' first adoption of AI is known as behavioural intention, and it can influence the course of their subsequent use.

Users' desire to use information technology is, in fact, the most significant driver of their usage behaviour, according to a number of empirical research carried out in various technology usage situations (e.g., Sheppard et al, 1988). When it comes to IT continuance, people are more likely to stick with a technology if they have good intentions about using it going forward, whether that be in online carbon footprint calculators (Lin, 2017), AI-based CRM systems (Chatterjee et al., 2021), or mobile banking (Nguyen and Dao, 2024). Thus, the following hypothesis was put out in this study:

H9: Behavioral intention positively influences continuance intention to use AI.

2.4.9. The moderating Impact of Shariah Compliance Perception (SCP)

It's common to use the terms religion, religiosity, and shariah compliance interchangeably. Religion affects people's values and views. Shariah compliance is strongly linked to a person's religion. A person's beliefs are a reflection of their knowledge on a certain topic (Arafa et al., 2021).

According to Al-Sartawi et al. (2022), Islamic banks function within a theological framework that is consistent with the ideals of their customers. They can increase user's satisfaction and confidence in the organization by keeping moral and Sharia-compliant practices (Anisykurlillah et al., 2020). Users satisfaction increases because of the fact that Customers and the bank have a strong emotional bond (Suhartanto et al., 2020).

Based on shariah compliance, research indicates that customers have good perceptions towards Islamic financial services, which have a statistically significant influence on their propensity to utilize them (Zinser, 2019). According to Charag (2020) Shariah compliance is a significant factor in determining customer attitude and desire to utilize Islamic banking. Similarly, Suhartanto et al. (2018) discovered that Islamic bank customers' desire to remain loyal is influenced by the banks' adherence to shariah. Technology adoption may be influenced by religious beliefs. One of the main factors affecting someone's decision to purchase goods or services is adherence to shariah. It affects individual attitudes, awareness, interactions, and purchasing/using behaviour (Suhartanto et al., 2020). The adoption of metaverse technology can also be influenced by religious communities (Alkhowaiter, 2022). As a result, we postulate the following:

H10: Shariah Compliance Perception positively moderates the relationship between Perceived ease of Use and Attitude towards AI.

H13: Shariah Compliance Perception positively moderates the relationship between Awareness towards AI and Attitude towards AI.

H16: Shariah Compliance Perception positively moderates the relationship between Subjective Norm and Attitude towards AI.

H19: Shariah Compliance Perception positively moderates the relationship between Perceived usefulness and Attitude towards AI.

H22: Shariah Compliance Perception positively moderates the relationship between Attitude towards AI and Behavioral Intension.

H25: Shariah Compliance Perception positively moderates the relationship between Behavioral Intension and Continuance Intension.

2.4.10. The moderating Impact of Perceived Risk (PR)

Recent study has looked at perceived risk as a factor affecting technology adoption, particularly in cases where privacy and security concerns are prevalent. Certain financial, product, performance, social, psychological, physical, time, privacy, or security concerns that arise during online transactions are referred to as perceived risks. These risks are present and become even more complex in the context of artificial intelligence (AI), as users may be afraid to enter their personal information due to potential security flaws in the system or may feel that they cannot rely on the system to always function properly and without technical issues, which could disrupt their educational experience. These facts led researchers to confirm that consumers' inclination to use technology is negatively impacted by perceived danger because of their bad behavior. Based on another study perceived risk by customers related to the new technology decreases their intention to use even if they see it easy to use a useful (Sasongko, 2025). Perceived risk in some studies considered as the main variable in shaping customer's attitude about the technology (Purwanegara et al. 2014). Perceived risk has also been shown to have a noteworthy impact on consumer attitude via perceived usefulness and ease of use (Akturan and Tezcan, 2012).

A lot of studies show that the business community is more aware of the benefits of AI than is commonly assumed. However, they agree that there are considerable impediments to AI adoption. The primary reasons for firms' rejection of this technology were a lack of necessary resources and an unwillingness to adapt. Even if AI has the potential to be widely used in corporate operations, its effectiveness is dependent on how users and industry perceive it and how loyal they are. It is thought that inaccurate or partial information may cause people to misunderstand artificial intelligence and develop a bad attitude towards it (Ryzhkova, 2020).

Customers' perceptions of AI vary. According to market research, even though a large number of consumers were aware of the term artificial intelligence (AI), they were unsure of its precise meaning because they had heard of it but were unable to define it or identify the precise uses for which it could be applied. This suggests that unfavorable attitudes and behaviors surrounding the acceptance and intention to use of currently accessible technology are caused by a lack of information about it (Ryzhkova, 2020). According to some studies, attitudes, awareness, behavioral intentions, and the continuation of technology use in using banking services online (Kaur & Arora, 2022), bank services provided through mobile application (Saibaba, 2024), services of pharmacy provide online (Alsadoun et al., 2023), and smart online grocery shopping (Thomas-Francois & Somogyi, 2023) are badly impacted by perceived risk. In light of these studies, we postulated the following:

H11: Perceived Risk negatively moderates the relationship between Perceived ease of Use and Attitude towards AI.

H14: Perceived Risk negatively moderates the relationship between Awareness towards AI and Attitude towards AI.

H17: Perceived Risk negatively moderates the relationship between Subjective Norm and Attitude towards AI.

H20: Perceived Risk negatively moderates the relationship between Perceived usefulness and Attitude towards AI.

H23: Perceived Risk negatively moderates the relationship between Attitude towards AI and Behavioral Intension.

H26: Perceived Risk negatively moderates the relationship between Behavioral Intension and Continuance Intension.

2.4.11. The moderating Impact of Perceived Trust (PT)

Quan et al. (2023) assert that a consumer's comfort, confidence, and assurance in using new technology are all related to trust. It determines whether people feel comfortable accepting new technologies and is a fundamental component of acceptance and adoption (Akther and Nur, 2022). Trust is crucial in digital business, because intangibility is a given. This kind of trust lowers doubts and concerns by encouraging users to interact responsibly (Shin and Rice, 2022).

It is crucial for users and suppliers to have mutual trust. Trust guarantees long-term confidence in new endeavours and strengthens user-provider connections (Sukumaran et al., 2022). Sasongko et al. (2022) define trust as the readiness of users to take on risks related to a third party's (like a bank's) transactions in the expectation that the bank would act in their best interests. Essentially, trustworthy organisations reduce risks and promote experimentation and adaptation.

Researchers suggested that trust is an important direct predictor of continuing intention in the context of mobile payment settings and online purchasing (Poromatikul et al., 2020). Positively inclined individuals exhibit a greater propensity for acceptance, depending on elements such as trust and related security protocols (Völter et al., 2021). As a result, trust becomes a critical component that affects user behaviour, especially when it comes to the usability and simplicity of technology (Deebak et al., 2022).

The development of social interactions over time has brought attention to the need of ongoing trust in the adoption of new technologies (Matemba and Li, 2018). Increased confidence generally accelerates the adoption rate of innovations, particularly those that are still in their infancy, according to studies like those conducted by Hasan et al. (2022). According to Nguyen and Ha (2021), trust probably lowers users' perceptions of danger and reluctance, promotes early use (pre-adoption), makes it possible for users to utilise financial services, and results in continued use.

Few studies have examined trust's moderating effect in the financial sector, despite the fact that it is examined as a dependent factor in a restricted number of scenarios (Ashique Ali and Subramanian, 2022). One important finding from earlier studies is that users become less risk averse and more vulnerable to dangers when their trust wanes (Sukumaran et al., 2022). Additionally, trust represents a higher degree of confidence in the use of digital technology by protecting customers' financial and personal information (Tan and Saraniemi, 2022). Furthermore, prior studies have shown that the link between subjective norm and continuance intention is

efficiently mediated by trust (Dewi & Ketut, 2020). The following hypothesis was put out in this study based on an analysis of earlier research:

H112: Perceived Trust positively moderates the relationship between Perceived ease of Use and Attitude towards AI.

H15: Perceived Trust positively moderates the relationship between Awareness towards AI and Attitude towards AI.

H18: Perceived Trust positively moderates the relationship between Subjective Norm and Attitude towards AI.

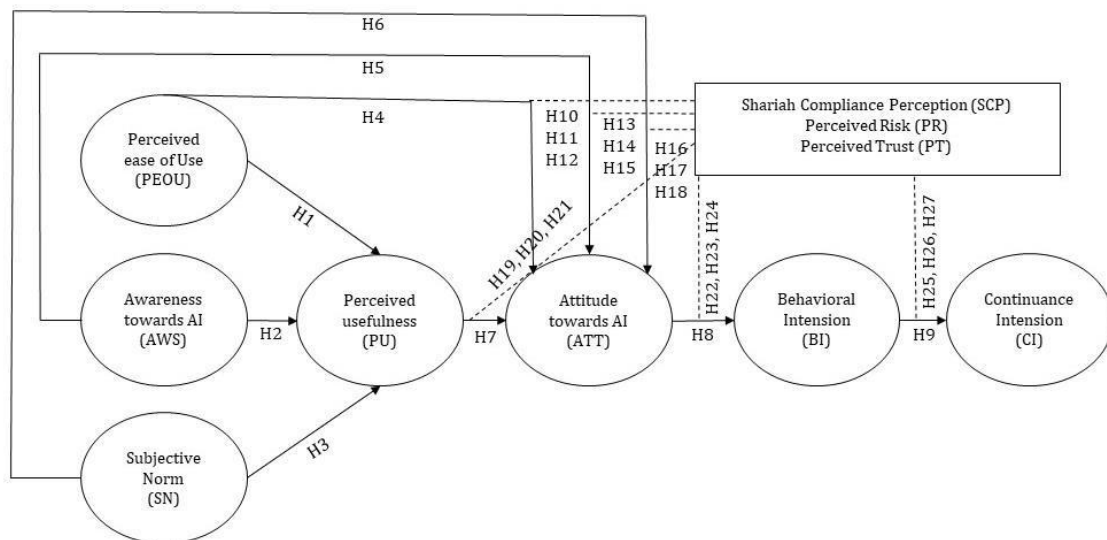
H21: Perceived Trust positively moderates the relationship between Perceived usefulness and Attitude towards AI.

H24: Perceived Trust positively moderates the relationship between Attitude towards AI and Behavioral Intension.

H27: Perceived Trust positively moderates the relationship between Behavioral Intension and Continuance Intension.

Conceptual Framework

Figure 1



3. METHODOLOGY

3.1. Research Design

We employed a quantitative, explanatory research technique in this work to ascertain the link amid the variables having an impact on the application of AI technology in Islamic banking. The TAM framework has been extended with the extra variable of Shariah compliance perception serving as a moderator in a deductive way. In order to collect statistical data, Islamic bank customers will be requested to fill out a standardized questionnaire with a cross-sectional temporal horizon. The literature will be supported by online publications.

3.2. Data Collection

To fully understand customer experiences and viewpoints on AI adoption in Islamic banks, this study employs a quantitative approach. Since our target audience is tech-savvy, we will only use online platforms to gather quantitative data through structured questionnaire that is given to a broader sample of Islamic bank clients.

3.3. Sample Selection

- **Population:** Banking service users of Pakistan were chosen for this study based on their interest in digital technology and familiarity with internet use.
- **Sample size:** A total of 350 respondents made up the study's sample size.
- **Sampling technique:** Purposive sampling is used in this study. This approach entails purposefully choosing volunteers according to certain standards pertinent to the study's goals.

3.4. Measurements and Social Disability Bias

The model framework representing the 10 variables in this study, each of which was assessed by three to four items, resulting in 37 questions. In the context of using AI in Islamic banking, each variable measurement is reflective, modified from a number of earlier studies, and corrected for accuracy of expression (Table 1 and Appendix). Banking professionals were contacted throughout the questionnaire's preparation in order to enhance each question's language appropriateness, measurement precision, and readability.

Table 1. Latent Variable Measurement

Variables	Questions	Modified from Source
Perceived ease of Use (PEOU)	4	Asnakew (2021)
Awareness towards AI (AWS)	4	Abou-Shouk and Soliman (2021)
Subjective Norm (SN)	4	Li'ebana-Cabanillas (2021)
Perceived usefulness (PU)	4	Li'ebana-Cabanillas (2021)
Attitude towards AI (ATT)	3	Asnakew (2021)
Behavioral Intension (BI)	3	Rahi et al. (2021)
Continuance Intension (CI)	3	Rahi et al. (2021)
Perceived Risk (PR)	4	Ben Arfi et al. (2021) and Jiang et al. (2021)
Perceived Trust (PT)	4	Li'ebana-Cabanillas (2021)
Shariah Compliance Perception (SCP)	4	Islam et al. (2015)

The research questionnaire was based on three sections. The first section included a statement about information confidentiality and motivated the respondents to answer the statements honestly (no wrong or correct answers). The second section contained the respondents' demographics, such as sex, age, education level, and occupation. Furthermore, concerning social disability bias, the research questionnaire did not include respondents' data (e-mail, name, and cell phone number). The third section contained a list of questions on a Likert-type semantic differential scale, with 1 representing strongly agree and 5 denoting strongly disagree (Appendix). Finally, the questionnaire was then generated on Google form and for collecting respondent's responses, it was distributed online through different media platforms such as Email, Facebook, WhatsApp and Instagram for two months (March–April 2025). This distribution was aimed at gathering data from a specific group of respondents who volunteered to participate in the study without compensation.

3.5. Common Method Bias

Collecting statistical data from Structured surveys are a very common data collection technique. The selected variables used in questionnaire based studies are operationalized through a number of items that constitute a previously established or newly developed scale. While being one of the most commonly used methods surveys also pose a threat of common method bias that can affect the reliability and validity of the empirical results and derived conclusions of a study. CMB can occur when both the independent and dependent variables are measured within one survey, using the same response method (e.g., ordinal scales). Therefore, CMB measurement was vital for supporting the validity of this study (Kock et al., 2021). We tested for CMB using the whole collinearity method based on latent variable score (LVS) data for all constructs. Thereafter, the LVS value was regressed with its random value to produce a variance inflation factor (VIF) value. The occurrence of a VIF greater than 3.3 indicates that a model may be contaminated by CMB. Therefore, if all VIFs resulting from a full collinearity test are equal to or lower than 3.3, the model can be considered free of CMB (Kock, 2015).

Table 2 presents the summary of CMB testing using SmartPLS 4.1.0.6. The VIF value for each measured variable was <3.3; thus, the research data were without collinearity problems.

Table 2. Common Method Bias

Latent Variables	VIF
Perceived ease of Use (PEOU)	1.373
Awareness towards AI (AWS)	1.294
Subjective Norm (SN)	1.172
Perceived usefulness (PU)	1.659
Attitude towards AI (ATT)	1.105
Behavioral Intension (BI)	1.037
Perceived Risk (PR)	1.062
Perceived Trust (PT)	1.090
Shariah Compliance Perception (SCP)	1.100

3.6. Normality

We used Structural Equation Modeling (SEM) that enable researchers to simultaneously model and estimate complex relationships among multiple dependent and independent variables, from this we tested statistical hypothesis using partial least squares structural equation modeling (PLS-SEM) that is used in exploratory research for developing a model with limited sources of the construct's theory; data do not have to be normally distributed and do not need to meet goodness-of-fit criteria and it's based on bootstrapping techniques (Hair Jr et al., 2021). To avoid the unsatisfactory statistical significance of the parameters in case of highly abnormal data researchers using PLS-SEM should assess data normality (Sarstedt et al., 2022).

The normality of the data was evaluated using the Skewness and Kurtosis tests from the raw data SmartPLS 4.1.0.6, with the value limits for Skewness and Kurtosis as -2 to $+2$. Table 3 presents a summary of the normality test results.

Table 3. Data Normality

Variables	Indicator	Kurtosis	Skewness
Perceived ease of Use	PEOU1	10.105	-0.309
	PEOU2	2.506	-1.19
	PEOU3	8.463	-1.229
	PEOU4	3.383	-1.504
Awareness towards AI	AWS1	2.454	-0.697
	AWS2	1.944	-0.622
	AWS3	3.429	0.024
	AWS4	1.905	0.024
Subjective Norm	SN1	1.463	0.061
	SN2	2.354	0
	SN3	1.524	0.036
	SN4	1.772	-0.357
Perceived usefulness	PU1	7.061	-0.448
	PU2	6.318	0
	PU3	2.029	-0.13
	PU4	6.392	0.759
Attitude towards AI	ATT1	11.723	0.509
	ATT2	3.787	0.167
	ATT3	6.361	1.274
Behavioral Intension	BI1	2.939	0.652
	BI2	2.989	0.062
	BI3	3.224	0.384

Continuance Intension	CI1	2.184	0.854
	CI2	4.536	0.602
	CI3	2.346	0.092
Perceived Risk	PR1	-0.04	0.011
	PR2	-0.052	0.066
	PR3	0.016	-0.035
	PR4	-0.116	-0.096
Perceived Trust	PT1	3.265	0.284
	PT2	5.174	0.383
	PT3	2.942	0.271
	PT4	4.523	-0.105
Shariah Compliance Perception	SCP1	9.247	-1.397
	SCP2	5.85	0
	SCP3	5.569	0.422
	SCP4	2.424	-0.941

Based on Table 3, some questions in each latent construct are abnormally distributed because the Skewness and Kurtosis values exceeded -2 or $+2$, and some items are typically distributed. This implies that the overall data do not indicate a highly abnormal problem. Therefore, selecting PLS-SEM to answer the research hypotheses is appropriate.

3.7. Confirmatory Factor Analysis

The consistency of the link between the observable variables and their underlying latent components was investigated using CFA. Maintaining the validity and dependability of the constructs in the research requires this kind of analytical rigour. Because SmartPLS is effective at handling high complexity while guaranteeing the reliability of the resulting outer loadings, T-statistics, and P-values for each variable, it was used to run the CFA in this study.

Table 4. Confirmatory Factor Analysis

Variable	Item	Mean	SD	Outer loading	T-value	P-value
Perceived ease of Use	PEOU1	0.806	0.040	0.809	20.456	0.000
	PEOU2	0.829	0.028	0.829	30.127	0.000
	PEOU3	0.824	0.038	0.827	21.973	0.000
	PEOU4	0.809	0.035	0.810	23.221	0.000
Awareness towards AI	AWS1	0.881	0.020	0.882	43.231	0.000
	AWS2	0.875	0.022	0.877	40.562	0.000
	AWS3	0.842	0.030	0.843	28.262	0.000
	AWS4	0.883	0.018	0.883	49.818	0.000
Subjective Norm	SN1	0.857	0.022	0.858	38.691	0.000
	SN2	0.853	0.026	0.855	32.776	0.000
	SN3	0.858	0.023	0.859	38.145	0.000
	SN4	0.857	0.023	0.859	37.252	0.000
Perceived usefulness	PU1	0.801	0.035	0.803	22.629	0.000
	PU2	0.787	0.039	0.789	20.457	0.000
	PU3	0.826	0.023	0.826	35.184	0.000
	PU4	0.775	0.037	0.776	21.068	0.000
Attitude towards AI	ATT1	0.735	0.050	0.739	14.733	0.000
	ATT2	0.823	0.027	0.824	29.967	0.000
	ATT3	0.806	0.035	0.807	23.023	0.000

Behavioral Intension	BI1	0.828	0.026	0.829	32.046	0.000
	BI2	0.817	0.027	0.817	29.880	0.000
	BI3	0.844	0.024	0.845	34.546	0.000
Continuance Intension	CI1	0.797	0.031	0.797	25.615	0.000
	CI2	0.824	0.033	0.825	24.843	0.000
	CI3	0.860	0.020	0.860	43.017	0.000
Perceived Risk	PR1	0.840	0.107	0.873	8.132	0.000
	PR2	0.823	0.105	0.833	7.936	0.000
	PR3	0.870	0.093	0.893	9.579	0.000
	PR4	0.876	0.088	0.897	10.138	0.000
Perceived Trust	PT1	0.807	0.167	0.881	5.277	0.000
	PT2	0.753	0.200	0.727	3.632	0.000
	PT3	0.811	0.163	0.878	5.384	0.000
	PT4	0.814	0.155	0.858	5.518	0.000
Shariah Compliance Perception	SCP1	0.707	0.182	0.773	4.253	0.000
	SCP2	0.792	0.173	0.864	4.984	0.000
	SCP3	0.741	0.193	0.802	4.152	0.000
	SCP4	0.796	0.183	0.852	4.664	0.000

According to statistics, outer loadings are considered significant when P-values are less than 0.05 and T-statistics are greater than 1.96, confirming a 95% confidence level (Hair et al., 2021). The CFA validates that these constructs accurately reflect the theoretical notions being studied, and our analysis, which is displayed in Table 4, demonstrates that every item satisfies these strict requirements, supporting the validity of the measuring model.

Table. Descriptive Statistics				
Variables	Questions		Descriptive Stats	
			Mean	Std
Perceived ease of use	1	I can easily use AI features and services provided by the Islamic bank.	1.991	0.278
	2	The Islamic bank's AI features and services are easily accessible to me.	1.880	0.382
	3	I quickly learn how to use the AI features and services provided by the Islamic bank.	1.960	0.290
	4	I find the Islamic bank's AI features and services are appropriate for my transactions.	1.891	0.354
Awareness of AI	5	I want to learn more about Islamic banks' AI features and services.	1.906	0.407
	6	I will pay more attention to Islamic banks that provide AI features and services.	1.894	0.425
	7	AI features and services in Islamic banking attract my attention.	2.003	0.396
	8	I am highly concentrated on AI features and services provided by Islamic banks.	2.006	0.454
Subjective Norm	9	The people whose opinions I value will approve if I use AI features and services for Islamic banking transactions.	2.020	0.475
	10	Most people I have in mind think I should use AI features and services for Islamic banking transactions.	2.000	0.434
	11	They expect me to use AI features and services for banking transactions.	2.011	0.472
	12	The people closest to me will agree if I use AI features and services for Islamic banking transactions.	1.920	0.446
Perceived Usefulness	13	Using AI features and services can help me perform Islamic banking transactions.	1.980	0.316
	14	Using AI features and services can increase efficiency in conducting Islamic banking transactions.	2.000	0.330
	15	Using AI features and services for Islamic banking transactions can increase my productivity.	1.971	0.446
	16	In general, AI features and services can help me with Islamic banking transactions.	2.037	0.323
Attitude toward AI	17	I think using the Islamic bank's AI features and services is a good idea.	2.011	0.262
	18	I think using the bank's AI features and services is fun.	2.017	0.385
	19	Using the Islamic bank's AI features and services for banking transactions is a desirable.	2.057	0.316
Behavioral Intention	20	I will use the Islamic bank's AI features and services regularly in the future.	2.077	0.396
	21	I recommend that others use AI Islamic banking features and services.	2.009	0.410
	22	I intend to use AI features and services to access my bank information easily.	2.046	0.397
Continuance Intention	23	I intend to continue using the Islamic bank's AI features and services rather than traditional ones.	2.114	0.405
	24	I want to continue using the Islamic bank's AI features and services as often as possible.	2.046	0.360
	25	I intend to continue using the Islamic bank's AI features and services rather than discontinuing them.	2.017	0.434
	26	Using AI features and services for Islamic banking transactions is risky.	2.940	0.740

Perceived Risk	27	Using AI tools and services for Islamic banking transactions will cause problems if something goes wrong.	3.140	0.764
	28	I will make a mistake using AI features and services for Islamic banking transactions.	3.077	0.735
	29	I feel worried about losing personal data.	3.014	0.787
Perceived Trust	30	Islamic Banks will keep their promises and commitments to AI features and services.	2.034	0.399
	31	AI features and services are trustworthy.	2.026	0.350
	32	I will convince myself that AI features and services are reliable systems.	2.037	0.409
	33	The Islamic bank will take responsibility for AI features and services.	1.991	0.366
Shariah Compliance Perception	34	AI in Islamic banking should operate in full compliance with Islamic Shariah principles.	1.960	0.280
	35	AI-driven banking solutions should exclusively support Shariah-compliant products and services.	2.000	0.338
	36	AI should be used to enhance the management and transparency of profit-sharing investment products in Islamic banking.	2.026	0.341
	37	AI technology can help Islamic banks operate without engaging in interest-based transactions.	1.889	0.395

3.8. Data analysis

In this research to justify our proposed hypothesis, we used PLS-SEM technique with SmartPLS 4.1.0.6 software for analysis. In this software two measurement models are used and are essential for validating our research model.

The first is, outer model, which deals with the relationship between the latent variables and survey items and is used to prove as if the items present in our questionnaire properly measure the theoretical variables. Testing techniques for outer model are Convergent validity (outer loading > 0.7), Cronbach's alpha and Composite Reliability (CA/CR > 0.7); an Average Variance Extracted (AVE > 0.5), discriminant validity refers to the Heterotrait-Monotrait ratio of correlations (HTMT < 0.85 or 0.9) and Fornell Lacker Criterion.

The second is, inner model, which deals with the latent variables themselves and is used to test the hypothesis to identify how significantly variables are related with other variables, using a bootstrapping two-tailed testing with the confidence interval technique. Testing techniques for inner model are Collinearity Statistics (VIF < 5), Path Coefficients (t-value/ p-value), Coefficient of Determination (R^2), Effect Size (f^2) and Predictive Relevance ($Q^2 > 0$).

4. Results

4.1. Respondents Profile

We targeted 390 responses from bank customers; 350 responses that met the sample criteria were obtained during the questionnaire distribution process. Therefore, the success rate of data collection was 90 %. The demographics of the respondents were obtained using the questionnaire results (Table 5). There were 212 (60.6 %) male and 138 (39.4 %) female respondents. Regarding age, 135 (38.6 %) were Below 30, 176 (50.3 %) were 30-39 and 39 (11.1 %) were 40-49 years old. 46 respondents (13.1 %) had bachelor degree, 16 (4.6 %) had a postgraduate degree, and 288 (82.3%) had a master degree. Regarding occupation, 38 (10.9 %) worked as government employees, 187 (53.4%) were private employee, 85 (24.3 %) were professionals, and 40 (11.4%) were unemployed.

Table 5. Respondent Characteristics		
Demographic Variables	N	Percentage
SEX		
Male	212	60.6%
Female	138	39.4%
AGE		
Below 30	135	38.6%
30-39	176	50.3%
40-49	39	11.1%
EDUCATION		
Bachelor	46	13.1%
Postgraduate	16	4.6%
Master's degree & above	288	82.3%
OCCUPATION		
Government employee	38	10.9%
Private employee	187	53.4%
Professional	85	24.3%
Unemployed	40	11.4%

4.2. Model Fit

Table 6. Model Fit		
	Saturated model	Estimated model
SRMR	0.048	0.057
d_ULS	1.599	2.256
d_G	0.669	0.697
Chi-square	1404.906	1455.480
NFI	0.795	0.787

The model fit indices for the estimated and saturated models in the PLS-SEM study are shown in Table 6. A satisfactory model fit between the observed and anticipated correlations is shown by the Standardised Root Mean Square Residual (SRMR) values for the saturated model (0.048) and the estimated model (0.057), both of which are below the acceptable threshold of 0.08 (Hu & Bentler, 1999). In comparison to the saturated model (1.599 and 0.669), the estimated model's d_ULS (squared Euclidean distance) and d_G (geodesic distance) values are marginally higher (2.256 and 0.697, respectively), indicating a slight increase in the difference between the empirical and model-implied correlation matrices. However, these values are still considered acceptable because of no strict threshold. Since big samples are predicted to have relatively high chi-square values; for saturated model 1404.906 and 1455.480 for the estimated model, this is not necessarily a sign of poor PLS-SEM fit. Lastly, the saturated model's and the estimated model's Normed Fit Index (NFI) are 0.795 and 0.787, respectively (Bentler & Bonett, 1980). These values fall just short of the optimal cut-off of 0.90 but are still within a reasonable range for complicated models. Together, these indices show that the suggested model fits the data satisfactorily, confirming the validity of the linkages that have been hypothesized inside the structural model.

4.3. Measurement Model

4.3.1. Validity and Reliability

The questionnaire was declared valid and reliable to answer the research objectives. Table 7 summarizes the convergent validity and reliability results. Statistically, each measurement item produces an outer loading value of >0.70 and an AVE of >0.50 . These values indicate that all the measurement items reflect the measured construct. Thus, convergent validity was declared. Furthermore, each latent construct produced CA and CR values of >0.70 , and none exceeded 0.950 (Hair Jr et al., 2022). This value indicates that each item is reliable for measuring the latent constructs.

Table 7. Validity and Reliability

Variable	Item	Outer loading	AVE	Cronbach's alpha (CA)	Composite reliability (CR)
Perceived ease of Use	PEOU1	0.809	0.670	0.836	0.891
	PEOU2	0.829			
	PEOU3	0.827			
	PEOU4	0.810			
Awareness towards AI	AWS1	0.882	0.759	0.895	0.926
	AWS2	0.877			
	AWS3	0.843			
	AWS4	0.883			
Subjective Norm	SN1	0.858	0.736	0.881	0.918
	SN2	0.855			
	SN3	0.859			
	SN4	0.859			
Perceived usefulness	PU1	0.803	0.638	0.810	0.875
	PU2	0.789			
	PU3	0.826			
	PU4	0.776			
Attitude towards AI	ATT1	0.739	0.625	0.700	0.833
	ATT2	0.824			
	ATT3	0.807			
Behavioral Intension	BI1	0.829	0.690	0.775	0.870
	BI2	0.817			
	BI3	0.845			
Continuance Intension	CI1	0.797	0.685	0.771	0.867
	CI2	0.825			
	CI3	0.860			
Perceived Risk	PR1	0.873	0.765	0.899	0.929
	PR2	0.833			
	PR3	0.893			
	PR4	0.897			
Perceived Trust	PT1	0.881	0.703	0.884	0.904
	PT2	0.727			
	PT3	0.878			
	PT4	0.858			
Shariah Compliance Perception	SCP1	0.773	0.678	0.847	0.894
	SCP2	0.864			
	SCP3	0.802			

4.3.2. Discriminant Validity

The discriminant validity was tested using the HTMT and Fornell Lacker Criterion methods. We assessed discriminant validity with the Fornell Lacker Criterion test, the root AVE value was greater than the correlation between the other constructs see Table 8.

Table 8. Fornell Lacker Criterion										
	ATT	AW	BI	CI	PEOU	PR	PT	PU	SCP	SN
ATT	0.791									
AW	0.342	0.871								
BI	0.619	0.333	0.831							
CI	0.500	0.244	0.641	0.828						
PEOU	0.291	-0.062	0.275	0.253	0.819					
PR	0.005	0.064	0.080	0.032	-0.065	0.874				
PT	-0.057	0.120	-0.042	-0.071	-0.049	0.022	0.838			
PU	0.500	0.310	0.446	0.358	0.375	-0.034	-0.032	0.798		
SCP	-0.092	-0.085	-0.038	-0.032	0.056	0.042	0.023	-0.006	0.823	
SN	0.282	-0.021	0.265	0.232	0.071	0.052	-0.103	0.297	-0.011	0.858

Similarly, with HTMT results in all correlation values between constructs less than 0.85 or 0.90 (Hair Jr et al., 2022) see Table 9. These results imply that the constructs with their indicators are more potent when measuring different constructs. Therefore, discriminant validity was confirmed.

Table 9. HTMT										
	ATT	AW	BI	CI	PEOU	PR	PT	PU	SCP	SN
ATT										
AW	0.421									
BI	0.837	0.394								
CI	0.680	0.292	0.825							
PEOU	0.379	0.074	0.340	0.310						
PR	0.036	0.071	0.098	0.042	0.086					
PT	0.061	0.116	0.054	0.071	0.059	0.052				
PU	0.663	0.361	0.559	0.446	0.454	0.070	0.061			
SCP	0.111	0.117	0.060	0.058	0.072	0.073	0.064	0.052		
SN	0.355	0.051	0.320	0.278	0.088	0.060	0.116	0.349	0.042	

Noted: PEOU=Perceived ease of use; AWS = Awareness of AI; SN=Subjective norms; PU=Perceived usefulness; ATT = Attitude toward AI; BI=Behavioral Intention; PR = Perceived risk; PT = Perceived Trust; SCP= Shariah Compliance Perception; CI=Continuance intention.

4.4. Structural Model

4.4.1. Collinearity

Structural model is evaluated in five stages. The first stage assessed collinearity within the structural model. In Table 10, the VIF value for each path in the PLS model is <3.3 (Diamantopoulos & Siguaw, 2006) therefore, the structural model is free from collinearity challenges.

Hypothesis	Path	VIF
H1	Perceived ease of use → Perceived usefulness	1.009
H2	Awareness of AI → Perceived usefulness	1.004
H3	Subjective Norm → Perceived usefulness	1.005
H4	Perceived ease of use → Attitude toward AI	1.373
H5	Awareness of AI → Attitude toward AI	1.294
H6	Subjective Norm → Attitude toward AI	1.172
H7	Perceived usefulness → Attitude toward AI	1.659
H8	Attitude toward AI → Behavioral Intention	1.105
H9	Behavioral Intention → Continuance Intension	1.037
H10	Shariah Compliance Perception × Perceived ease of use → Attitude toward AI	2.630
H11	Perceived Risk × Perceived ease of use → Attitude toward AI	1.539
H12	Perceived Trust × Perceived ease of use → Attitude toward AI	1.259
H13	Shariah Compliance Perception × Awareness of AI → Attitude toward AI	1.344
H14	Perceived Risk × Awareness of AI → Attitude toward AI	1.347
H15	Perceived Trust × Awareness of AI → Attitude toward AI	1.163
H16	Shariah Compliance Perception × Subjective Norm → Attitude toward AI	1.267
H17	Perceived Risk × Subjective Norm → Attitude toward AI	1.102
H18	Perceived Trust × Subjective Norm → Attitude toward AI	1.192
H19	Shariah Compliance Perception × Perceived usefulness → Attitude toward AI	3.293
H20	Perceived Risk × Perceived usefulness → Attitude toward AI	1.747
H21	Perceived Trust × Perceived usefulness → Attitude toward AI	1.486
H22	Shariah Compliance Perception × Attitude toward AI → Behavioral Intention	1.133
H23	Perceived Risk × Attitude toward AI → Behavioral Intention	1.038
H24	Perceived Trust × Attitude toward AI → Behavioral Intention	1.161
H25	Shariah Compliance Perception × Behavioral Intention → Continuance Intension	1.159
H26	Perceived Risk × Behavioral Intention → Continuance Intension	1.030
H27	Perceived Trust × Behavioral Intention → Continuance Intension	1.142

4.4.2. Hypothesis Testing

The second stage involved testing hypothesis through path coefficient t-value and p-value provided in the table below. Nine direct hypothesis (Table 11) and eighteen indirect hypotheses (Table 12) were tested.

Table 11. Direct Hypothesis

Hypothesis	Path	Beta	T-value	P-value	Decision
H1	Perceived ease of use → Perceived usefulness	0.376	6.510	0.000	Accepted
H2	Awareness of AI → Perceived usefulness	0.339	6.474	0.000	Accepted
H3	Subjective Norm → Perceived usefulness	0.277	6.430	0.000	Accepted
H4	Perceived ease of use → Attitude toward AI	0.190	3.779	0.000	Accepted
H5	Awareness of AI → Attitude toward AI	0.258	4.624	0.000	Accepted
H6	Subjective Norm → Attitude toward AI	0.174	3.546	0.000	Accepted
H7	Perceived usefulness → Attitude toward AI	0.312	4.273	0.000	Accepted
H8	Attitude toward AI → Behavioral Intention	0.614	11.959	0.000	Accepted
H9	Behavioral Intention → Continuance Intension	0.637	14.014	0.000	Accepted

Hypothesis 1 (H1): Perceived ease of use (PEOU) -> Perceived usefulness (PU)

Beta value 0.378 shows a moderate positive relation between Perceived ease of use and Perceived usefulness while the high t-value 6.510 (> 1.96) and p-value < 0.001 confirms the statistical significance of this relationship. Thus the result supported the evidence that ease of using the AI technology increases the user's perception of its usefulness.

Hypothesis 2 (H2): Awareness of AI (AW) -> Perceived usefulness (PU)

Beta value 0.339 shows a moderate positive relation between Awareness of AI and Perceived usefulness while the high t-value 6.474 (> 1.96) and p-value < 0.001 confirms the statistical significance of this relationship. Thus the result supported the evidence that Awareness influence how useful users perceive AI technology to be.

Hypothesis 3 (H3): Subjective Norm (SN) -> Perceived usefulness (PU)

Beta value 0.277 shows a positive relation between Subjective Norm and Perceived usefulness while the high t-value 6.430 (> 1.96) and p-value < 0.001 confirms the statistical significance of this relationship. Thus the result supported the evidence that social influence slightly improves user's perception of usefulness.

Hypothesis 4 (H4): Perceived ease of use (PEOU) -> Attitude toward AI (ATT)

Beta value 0.190 shows a positive relation between Perceived ease of use and Attitude toward AI while the high t-value 3.779 (> 1.96) and p-value < 0.001 confirms the statistical significance of this relationship. Thus the result supported the evidence that easier the technology is perceived to use, the more positive user's attitude towards AI.

Hypothesis 5 (H5): Awareness of AI (AW) -> Attitude toward AI (ATT)

Beta value 0.258 shows a moderate positive relation between Awareness of AI and Attitude toward AI while the high t-value 4.624 (> 1.96) and p-value < 0.001 confirms the statistical significance of this relationship. Thus the result supported the evidence that increase Awareness about AI technology enhance user's attitude towards adopting it.

Hypothesis 6 (H6): Subjective Norm (SN) -> Attitude toward AI (ATT)

Beta value 0.174 shows a moderate positive relation between Subjective Norm and Attitude toward AI while the high t-value 3.546 (> 1.96) and p-value < 0.001 confirms the statistical significance of this relationship. Thus the result supported the evidence that social influence somewhat has a part in the formation of user's favorable attitude.

Hypothesis 7 (H7): Perceived usefulness (PU) -> Attitude toward AI (ATT)

Beta value 0.312 shows a moderate positive relation between Perceived usefulness and Attitude toward AI while the high t-value 4.273 (> 1.96) and p-value < 0.001 confirms the statistical significance of this relationship. Thus the result supported the evidence that the more useful AI technology is perceived the more favorable the attitude of users is.

Hypothesis 8 (H8): Attitude toward AI (ATT) -> Behavioral Intention (BI)

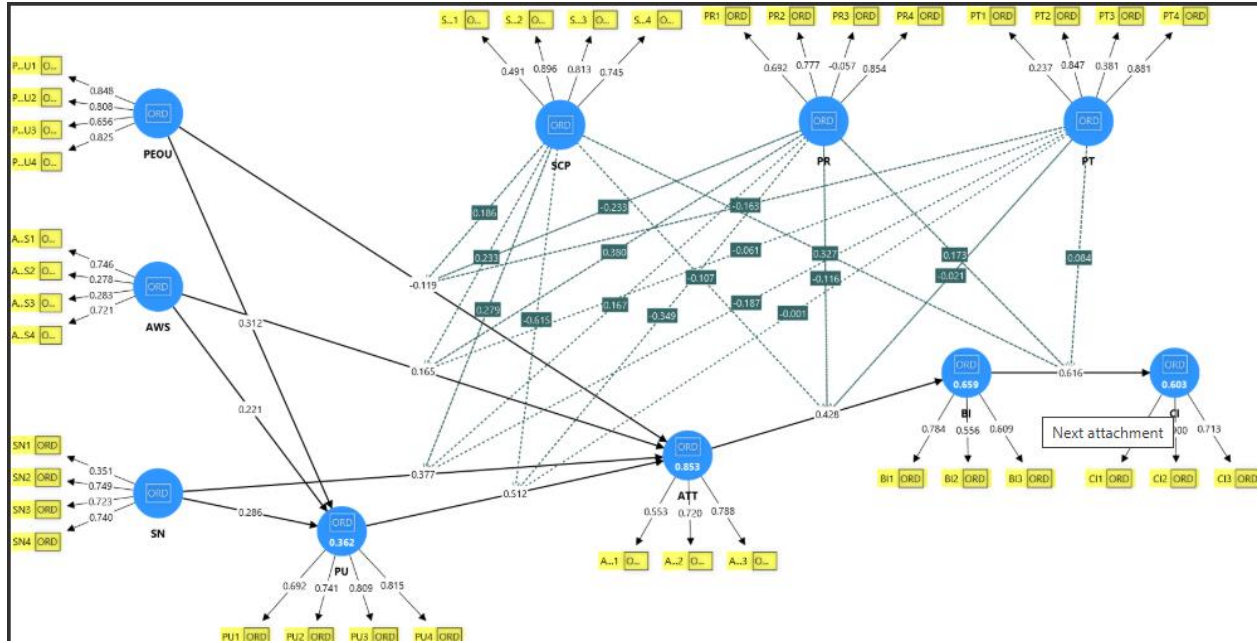
Beta value 0.614 shows a strong positive relation between Attitude toward AI and Behavioral Intention while the high t-value 11.959 (> 1.96) and p-value < 0.001 confirms the statistical significance of this relationship. Thus the result supported the evidence that user's attitude significantly drives the intention to use AI technology.

Hypothesis 9 (H9): Behavioral Intention (BI) -> Continuance Intension (CI)

Beta value 0.637 shows a strong positive relation between Behavioral Intention and Continuance Intension while the high t-value 14.014 (> 1.96) and p-value < 0.001 confirms the statistical significance of this relationship. Thus the result supported the evidence that a positive behavior leads to the continuance usage of AI technology in the future.

Table 12. Indirect Hypothesis

Hypothesis	Path	Beta	T-value	P-value	Decision
H10	Shariah Compliance Perception $\times$ Perceived ease of use $\rightarrow$ Attitude toward AI	0.003	0.042	0.966	Rejected
H11	Perceived Risk $\times$ Perceived ease of use $\rightarrow$ Attitude toward AI	0.032	0.622	0.534	Rejected
H12	Perceived Trust $\times$ Perceived ease of use $\rightarrow$ Attitude toward AI	-0.001	0.011	0.991	Rejected
H13	Shariah Compliance Perception $\times$ Awareness of AI $\rightarrow$ Attitude toward AI	0.040	0.410	0.682	Rejected
H14	Perceived Risk $\times$ Awareness of AI $\rightarrow$ Attitude toward AI	0.031	0.534	0.594	Rejected
H15	Perceived Trust $\times$ Awareness of AI $\rightarrow$ Attitude toward AI	-0.052	0.788	0.431	Rejected
H16	Shariah Compliance Perception $\times$ Subjective Norm $\rightarrow$ Attitude toward AI	-0.023	0.357	0.721	Rejected
H17	Perceived Risk $\times$ Subjective Norm $\rightarrow$ Attitude toward AI	-0.021	0.424	0.672	Rejected
H18	Perceived Trust $\times$ Subjective Norm $\rightarrow$ Attitude toward AI	-0.045	0.890	0.373	Rejected
H19	Shariah Compliance Perception $\times$ Perceived usefulness $\rightarrow$ Attitude toward AI	-0.036	0.301	0.764	Rejected
H20	Perceived Risk $\times$ Perceived usefulness $\rightarrow$ Attitude toward AI	-0.076	0.908	0.364	Rejected
H21	Perceived Trust $\times$ Perceived usefulness $\rightarrow$ Attitude toward AI	0.023	0.373	0.709	Rejected
H22	Shariah Compliance Perception $\times$ Attitude toward AI $\rightarrow$ Behavioral Intention	0.066	0.901	0.368	Rejected
H23	Perceived Risk $\times$ Attitude toward AI $\rightarrow$ Behavioral Intention	-0.094	1.268	0.205	Rejected
H24	Perceived Trust $\times$ Attitude toward AI $\rightarrow$ Behavioral Intention	-0.095	1.353	0.176	Rejected
H25	Shariah Compliance Perception $\times$ Behavioral Intention $\rightarrow$ Continuance Intension	-0.015	0.256	0.798	Rejected
H26	Perceived Risk $\times$ Behavioral Intention $\rightarrow$ Continuance Intension	-0.029	0.428	0.669	Rejected
H27	Perceived Trust $\times$ Behavioral Intention $\rightarrow$ Continuance Intension	-0.014	0.178	0.858	Rejected



Hypothesis 10 (H10): Shariah Compliance Perception (SCP) × Perceived ease of use (PEOU) → Attitude toward AI (ATT)

The path coefficient 0.003 implies a very low effect of the moderator on the relationship between Perceived ease of use and Attitude toward AI while with a t-value $0.042 < 1.96$ and an insignificant p-value of 0.966 interprets the hypothesis to be rejected showing that users may not base their attitude on religious principles within that usage context.

Hypothesis 11 (H11): Perceived Risk (PR) × Perceived ease of use (PEOU) → Attitude toward AI (ATT)

The beta value 0.032 shows a very weak effect of the moderator while with a t-value $0.622 < 1.96$ and an insignificant p-value of 0.534 rejected the hypothesis interpreting that even if the system is easy to use, concerns about its risk may not change the usability attitude.

Hypothesis 12 (H12): Perceived Trust (PT) × Perceived ease of use (PEOU) → Attitude toward AI (ATT)

The path coefficient -0.001 with t-value $0.011 < 1.96$ and an insignificant p-value of 0.991 rejected the hypothesis showing if users already have developed a favorable attitude because they perceive the system is easy to use then the level of trust may not impact much.

Hypothesis 13 (H13): Shariah Compliance Perception (SCP) × Awareness of AI (AW) -> Attitude toward AI (ATT)

The path coefficient 0.040 with t-value $0.410 < 1.96$ and an insignificant p-value of 0.682 rejected the hypothesis showing users could form positive attitude based on increase in awareness towards the AI technology rather than taking into account the religious principles.

Hypothesis 14 (H14): Perceived Risk (PR) × Awareness of AI (AW) -> Attitude toward AI (ATT)

The beta value 0.031 shows a very weak effect of the moderator while with a t-value $0.534 < 1.96$ and an insignificant p-value of 0.594 rejected the hypothesis interpreting that awareness of the AI technology does not always reduce perceived risk; this weakens the moderation effect on attitude.

Hypothesis 15 (H15): Perceived Trust (PT) × Awareness of AI (AW) -> Attitude toward AI (ATT)

The path coefficient -0.052 with t-value $0.788 < 1.96$ and an insignificant p-value of 0.431 rejected the hypothesis interpreting that even with awareness trust on the technology developed over time showing awareness does not amplify the effect of perceived trust on attitude.

Hypothesis 16 (H16): Shariah Compliance Perception (SCP) × Subjective Norm (SN) -> Attitude toward AI (ATT)

The beta value -0.023 shows a very weak effect of the moderator while with a t-value $0.357 < 1.96$ and an insignificant p-value of 0.721 rejected the hypothesis explaining user's attitude may remain same due to social pressure while separating the religious judgment from it.

Hypothesis 17 (H17): Perceived Risk (PR) × Subjective Norm (SN) -> Attitude toward AI (ATT)

The path coefficient -0.021 with t-value $0.424 < 1.96$ and an insignificant p-value of 0.672 rejected the hypothesis clarifying that social pressure may not mitigate concerns about AI in forming the attitude.

Hypothesis 18 (H18): Perceived Trust (PT) × Subjective Norm (SN) -> Attitude toward AI (ATT)

The beta value -0.045 shows a very weak effect of the moderator while with a t-value $0.890 < 1.96$ and an insignificant p-value of 0.373 rejected the hypothesis elucidating that even with societal support trust is only build based on experience while the users attitude is directly linked to subjective norm.

Hypothesis 19 (H19): Shariah Compliance Perception (SCP) × Perceived usefulness (PU) -> Attitude toward AI (ATT)

The path coefficient -0.036 with t-value $0.301 < 1.96$ and an insignificant p-value of 0.764 rejected the hypothesis clarifying users see AI as useful and shape a positive attitude while taking Shariah Compliance Perception as irrelevant.

Hypothesis 20 (H20): Perceived Risk (PR) × Perceived usefulness (PU) -> Attitude toward AI (ATT)

The path coefficient -0.076 implies negative effect of the perceived risk on the relationship between Perceived usefulness and Attitude toward AI while with a t-value $0.908 < 1.96$ and an insignificant p-value of 0.364 interprets the hypothesis to be rejected showing users take no effect of perceived risk while shaping a positive attitude in usability context.

Hypothesis 21 (H21): Perceived Trust (PT) × Perceived usefulness (PU) -> Attitude toward AI (ATT)

The beta 0.023 implies weak effect of the Perceived trust on the relationship between Perceived usefulness and Attitude toward AI while with a t-value $0.373 < 1.96$ and an insignificant p-value of 0.709 explaining the hypothesis to be rejected based on the fact that users form the attitude base on how useful they think the AI is while excluding the effect of perceived trust.

Hypothesis 22 (H22): Shariah Compliance Perception (SCP) × Attitude toward AI (ATT) -> Behavioral Intention (BI)

The path coefficient 0.066 implies weak effect of the Shariah Compliance on the relationship between Attitude toward AI and Behavioral Intention while with a t-value $0.901 < 1.96$ and an insignificant p-value of 0.368 explaining the hypothesis to be rejected elucidating that a positive attitude towards AI may not be influence by religious perception thus not impacting the behavioral towards its usage.

Hypothesis 23 (H23): Perceived Risk (PR) × Attitude toward AI (ATT) -> Behavioral Intention (BI)

The path coefficient -0.094 implies negative effect of the perceived risk on the relationship between Attitude toward AI and Behavioral Intention while with a t-value $1.268 < 1.96$ and an insignificant p-value of 0.205 clarifying the hypothesis to be rejected as positive attitude directly impact behavioral intention while perceive risk may independently deter usage.

Hypothesis 24 (H24): Perceived Trust (PT) × Attitude toward AI (ATT) -> Behavioral Intention (BI)

The beta value -0.095 shows negative effect of the perceived trust on the relationship between Attitude toward AI and Behavioral Intention while with a t-value $1.353 < 1.96$ and an insignificant p-value of 0.176 rejected the hypothesis explaining may be trust and attitude influence behavioral intention directly but not interactively.

Hypothesis 25 (H25): Shariah Compliance Perception (SCP) × Behavioral Intention (BI) -> Continuance Intension (CI)

The path coefficient -0.015 implies negative effect of Shariah Compliance on the relationship between Behavioral Intention and Continuance Intension while with a t-value $0.256 < 1.96$ and an insignificant p-value of 0.798 shows the hypothesis to be rejected explaining it might be as if users has already developed the intention to continuingly usage of AI in future that impact of Shariah Compliance might not matter.

Hypothesis 26 (H26): Perceived Risk (PR) × Behavioral Intention (BI) -> Continuance Intension (CI)

The beat value of -0.029 shows a negative effect of the moderator on the relationship between Behavioral

Intention and Continuance Intension while based on a t-value $0.428 < 1.96$ and an insignificant p-value of 0.669 hypothesis is rejected interpreting once behavior is intended; perceived risk might lose its influence on ongoing commitment.

Hypothesis 27 (H27): Perceived Trust (PT) × Behavioral Intention (BI) -> Continuance Intension (CI)

The beat value of -0.014 shows a negative effect of the moderator on the relationship between Behavioral

Intention and Continuance Intension while based on a t-value $0.178 < 1.96$ and an insignificant p-value of 0.858 hypothesis is rejected clarifying that it might be the reason that if the intention to continue usage of AI in future is already strong trust becomes less relevant.

4.4.3. R-value

The third assess explanatory power. The R-value is used to evaluate the explanatory power of the structural model. The coefficient represents the variance in the endogenous constructs explained by all exogenous constructs. It provides insights into the goodness of fit of a model, essentially showing how well the model explains the variability of the outcome variable. Values of R-square range from 0 to 1, with higher values indicating a better fit of the model to the data. In PLS-SEM, values above 0.25 are considered weak, 0.50 moderate, and 0.75 substantial (Hair Jr et al., 2022).

Table 13. R-Square			
	R-square	R-square adjusted	Assumption
ATT	0.362	0.326	Moderate
BI	0.404	0.391	Moderate
CI	0.415	0.403	Moderate
PU	0.328	0.322	Moderate

Table 13 displays 36.2% of the variance in attitude towards AI is explained by its predictors showing a moderate explanatory power; 40.4% of the variance in Behavioral intention is explained by its predictors showing a moderate explanatory power; 41.5% variance suggest that the model moderately predicts users intention to continue using the technology; and 32.8% of variance in Perceived usefulness shows slightly lower but acceptable explanatory power as it is influenced by moderate predictive construct.

4.4.4. F-Square

The fourth stage determined the strength of the relationship in the structural model which is assessed using the f^2 -effect size values through the contribution of each independent and dependent variable. The criteria for assessing the strength of the relationship between constructs in the structural model refer to the provisions: $f^2 = 0.02\text{--}0.14$ (weak), $f^2 = 0.15\text{--}0.34$ (moderate), and $f^2 \geq 0.35$ (strong) (Cohen, 2013).

Table 14. f-square		
Path	f^2	Decision
Perceived ease of use $\rightarrow$ Perceived usefulness	0.209	moderate
Awareness of AI $\rightarrow$ Perceived usefulness	0.170	moderate
Subjective Norm $\rightarrow$ Perceived usefulness	0.113	weak
Perceived ease of use $\rightarrow$ Attitude toward AI	0.041	weak
Awareness of AI $\rightarrow$ Attitude toward AI	0.081	weak
Subjective Norm $\rightarrow$ Attitude toward AI	0.040	weak
Perceived usefulness $\rightarrow$ Attitude toward AI	0.092	weak
Attitude toward AI $\rightarrow$ Behavioral Intention	0.572	strong
Behavioral Intention $\rightarrow$ Continuance Intension	0.668	strong
Shariah Compliance Perception $\times$ Perceived ease of use $\rightarrow$ Attitude toward AI	0.000	negligible effect
Perceived Risk $\times$ Perceived ease of use $\rightarrow$ Attitude toward AI	0.001	negligible effect
Perceived Trust $\times$ Perceived ease of use $\rightarrow$ Attitude toward AI	0.000	negligible effect
Shariah Compliance Perception $\times$ Awareness of AI $\rightarrow$ Attitude toward AI	0.001	negligible effect
Perceived Risk $\times$ Awareness of AI $\rightarrow$ Attitude toward AI	0.001	negligible effect
Perceived Trust $\times$ Awareness of AI $\rightarrow$ Attitude toward AI	0.003	negligible effect
Shariah Compliance Perception $\times$ Subjective Norm $\rightarrow$ Attitude toward AI	0.001	negligible effect
Perceived Risk $\times$ Subjective Norm $\rightarrow$ Attitude toward AI	0.001	negligible effect
Perceived Trust $\times$ Subjective Norm $\rightarrow$ Attitude toward AI	0.002	negligible effect
Shariah Compliance Perception $\times$ Perceived usefulness $\rightarrow$ Attitude toward AI	0.001	negligible effect
Perceived Risk $\times$ Perceived usefulness $\rightarrow$ Attitude toward AI	0.005	negligible effect
Perceived Trust $\times$ Perceived usefulness $\rightarrow$ Attitude toward AI	0.000	negligible effect
Shariah Compliance Perception $\times$ Attitude toward AI $\rightarrow$ Behavioral Intention	0.007	negligible effect
Perceived Risk $\times$ Attitude toward AI $\rightarrow$ Behavioral Intention	0.011	negligible effect
Perceived Trust $\times$ Attitude toward AI $\rightarrow$ Behavioral Intention	0.009	negligible effect
Shariah Compliance Perception $\times$ Behavioral Intention $\rightarrow$ Continuance Intension	0.000	negligible effect
Perceived Risk $\times$ Behavioral Intention $\rightarrow$ Continuance Intension	0.001	negligible effect
Perceived Trust $\times$ Behavioral Intention $\rightarrow$ Continuance Intension	0.000	negligible effect

Table 14 displays all the f^2 effect size values of direct and indirect hypothesis. The above analysis interprets the result of direct hypothesis as variables Perceived ease of use, Awareness of AI and Subjective norm showed moderate – weak influence on Perceived Usefulness with f^2 values of 0.209, 0.170, 0.11, respectively. Further Perceived ease of use, Awareness of AI and Subjective norm; along with Perceived Usefulness displayed weak effect on variable Attitude towards AI, with f^2 values 0.041,

0.081, 0.040 and 0.092, implying that they have a small but noticeable influence on user's Attitudes towards AI technology.

On the other hand, behavioral intention was strongly impacted by Attitude towards AI ($f^2 = 0.572$), and behavioral intention had an even more strongly impact on continuance intention ($f^2 = 0.668$). These high values show that people's attitudes greatly influence their desire to use it and their behavioral intention considerably predicts their continuous usage of AI technology.

Conversely, all indirect hypothesis; those involving moderators such as Shariah Compliance Perception, Perceived Risk, and Perceived Trust; showed insignificant f^2 values (all < 0.02). Their low explanatory ability in this context is shown by the suggestion that these moderating factors have almost little effect on the corresponding connections within the model.

5. DISCUSSION AND IMPLICATIONS

5.1. Discussion

The results of this interdisciplinary study add to the body of knowledge on consumers' perceptions of AI technology adoption in Islamic banking because it evaluated all of the assumptions that were put out. In this study TAM model was extended by adding moderating elements i.e. perceived risk, perceived trust, and Shariah compliance.

Empirical findings of this study proved a strong positive relation between Perceived ease of use (PEOU), Awareness towards AI (AWS), and subjective norms (SN) on perceived usefulness (PU) and Attitude towards the AI (ATT). Positive impact of these variables on Perceived usefulness (PU) influence the positive Attitude towards the AI (ATT) usage. A positive attitude leads toward behavior intentions (BI) and ultimately continued intention (CI) to use AI in the Islamic banking industry.

Hypothesis developed in this study showed that Perceived ease of use, AI awareness and subjective norms strongly influence the perceived usefulness. This interprets that users who perceive technology to be easy to use, have the knowledge of its applications and capabilities; that includes assistance in banking transactions, providing access of banking features and so on believe it to be useful in speeding their task completion. Moreover, social pressure, group discussions also impact the user's perception about technology usefulness. Recent researchers have also supported these statement. Users who have the knowledge of using mobile wallets based on AI accept its usefulness (Singh and Sinha, 2020). Perceived usefulness of the AI technology is influenced by subjective norm which in turn motivate the user and increase its intention to use (Rahman et al., 2023). The feature of chatbot in banking system help ease the process of inquiring banking information related to its services makes users satisfied leading to their positive perception related to its usefulness because it simplifies the discussion (Abdullah & Almaqtari, 2024).

Another variable attitudes towards AI hypothesis showed that Perceived ease of use, AI awareness, subjective norms and perceived usefulness all have a direct positive impact on it. This interprets

that user's positive attitude is developed based on how easy they perceive the system is, how much knowledge they have about its usage, how much social pressure they take while considering its adoption and how useful they perceive the technology is. Our all these results are supported by other researches as well (Kashive et al., 2021; Rahman et al., 2023; and Kasim & Wickens, 2020).

Attitudes towards AI also showed a positive direct relation with behavioral intention. A positive attitude towards the technology influence the user's intention to adopt or accept that system making a positive believe in his mind that AI technology is beneficial. Past studies also supported our result showing influence of attitude towards behavioral intention to use AI (Rahman et al., 2023 and Roy et al., 2022).

Behavioral intention showed a strong positive impact on continuance intention of using AI in Islamic banking. Other research's also proved that behavioral intention influence the continuance use of technology (Chatterjee et al., 2021).

While moderating construct used as an extension of the TAM model i.e. perceived risk, perceived trust, and Shariah compliance perception all got rejected, we assumed that may be these variables don't have any place as a moderator in the model or were not correctly linked because all the other independent and dependent variables are already strongly connected. It also interprets that consumers while making a choice in adopting AI services today or its continue usage in future is not influenced by the Islamic laws, perception of risk and trust of this artificial technology.

5.2. Implications

This study is acknowledged to have made two contributions. The first theoretical implication is creating a modified version of the TAM model to investigate user's perceptions related to the use of AI technology in Islamic banking, their behaviors intention on continuance using the service in the future. TAM has drawn a lot of criticism for ignoring the human and inhibiting components in favor of the technological and enabling ones. Therefore, the conceptual model of the study, which combines enabling, human, and technological components, is what makes it new. This study improves our knowledge of AI adoption in the banking industry and confirms the application of the TAM model. The study's conclusions contribute to the expanding corpus of research on the use of AI technology in Islamic banking. Furthermore, numerous studies have been conducted on this technology but only separate researches were seen that either look into Islamic banking, Islamic principles, moderating effects of either risk, trust or religion, AI adoption, TAM model; none of the study examined all of these variables in a unified model and their influence on consumers' decision to continue using AI in Islamic banks. Accordingly, this study is regarded as one of the first to use all TAM-related, enabling, human, Islamic, and technical factors in a single model. Therefore, the results of this study offer useful advice that can be used to the effective integration of AI technology into financial services.

Secondly, practical implications. This study is helpful for researchers and banking service providers as it provides the customer perspective information related to the use of AI and its adoption in Islamic banking sector. It shows user's perspective how easy technology should be, what information related to it is necessary, what type of social impact can influence its usage and usefulness. This study showed that using AI technology in banking improves the system capability, will help users to better understand its function and simplifies the banking features. To make AI accepted by their user's bank should focus on quality of their services, provide proper guidelines to better understand of its usage and promote AI applications for every service they provide to give users convenience of usage.

6. CONCLUSION

Considering all the research gaps mentioned in the literature, using Islamic bank feature of religiosity as an additional variable, taking inspiration from Ikhsan et al. (2025) research model and re-arranging the model variables and incorporating additional moderating variables of risk, trust and Shariah Compliance Perception relevant to Muslim cultural setting, into a unified framework of TAM; this research is carried out to understand customer attitudes and their intention to continue implementing AI in Islamic banking.

The study used quantitative, explanatory research technique, statistical data was collected from banking service users through a standardized questionnaire using an online platform in a cross-sectional temporal horizon. The literature is supported by online publications. A total of 350 respondents made up the study's sample size. Partial Least Squares Structural Equation Modelling (PLS-SEM) was used for data analysis. This research is based on AI adoption in Islamic banking through an extension of the Technology Acceptance Model (TAM) with perceived risk, perceived trust, and perception of Shariah compliance as moderators. The aim of this research was to find the impact of Perceived ease of use (PEOU), Awareness towards AI (AWS), and subjective norms (SN) on perceived usefulness (PU), which in turn affect attitude towards AI (ATT). A positive attitude leads toward behavior intentions (BI) and ultimately continued intention (CI). We also contend that perceived risk of AI (PR), perceived trust in AI (PT), and perception of Shariah compliance (SCP) moderate the effect of PEOU, AWS, SN and PU on ATT, the effect of ATT on BI, and the effect of BI on CI respectively, in a way that higher level of PR, PT, and SCP will make these relationships stronger.

The study's empirical findings clarify that all 9 direct hypotheses of variables perceived ease of use, awareness of AI, subjective norm, and perceived usefulness; positively impact attitudes, behaviors, and continuance intentions to use AI in the banking industry. The analysis also revealed that all of the 18 moderators' hypotheses from the extension of constructs from the TAM framework, including perceived risk, perceived trust, and Shariah compliance perception, were disproved suggesting that users do not give religious judgment, risk perception, or degree of trust much thought while deciding whether to keep utilizing AI technology in the Islamic banking

sector. The conclusions point to the importance of raising acceptability and adoption in Islamic banking by utilizing social influence, raising awareness, and easy-to-use AI solutions. The report provides valuable recommendations to researchers, financial institutions, and policymakers who wish to implement AI technology in a customer-oriented manner, alongside contributing to the growing literature on AI in banking and a better understanding of people's willingness to embrace AI-enabled banking solutions that are consistent with their ethical and religious convictions by providing thorough insights into customer perceptions and their intentions to stick with the service.

6.1. Limitation and Future Recommendation

Although offering revealing details, this research has several weaknesses that open the door to additional research. For starters, the results may not be as translatable to other regions or banking systems since the data was collected from a specific group within the Islamic banking sector. This can be modified in subsequent research by comparing conventional and Islamic financial institutions.

Second, the study employed a cross-sectional research design, which gathered responses simultaneously. The method has the drawback of making it harder to monitor how consumer behavior changes over time. It is suggested that future studies employ a longitudinal design to study how attitudes and perceptions towards AI change due to increased exposure and technological progress.

Third, the statistical rejection of all moderation hypotheses indicates that there may be a flaw in how these concepts were conceptually located or measured. Future research can re-measure these moderators under new operational definitions, assess their mediating or direct roles, or explore other contextspecific factors such as cultural orientation, digital literacy, and regulation support.

Fourth, the research relied solely on self-reported data, which could be methodologically biased by standard method variation or social desirability. Triangulation with actual behavioral data or mixedmethod approaches may enhance the depth and validity of the findings.

Lastly, AI products and emerging technologies continue to evolve rapidly. To provide more specific analyses, upcoming scholars may consider examining some of the AI products or services within Islamic finance.

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