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Adoption of artificial intelligence in banking services: an empirical analysis

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Abstract

Purpose – This study aims to understand the importance and challenges of adopting artificial intelligence (AI) in the banking industry in Malaysia and examine the factors that are important in investigating consumers' intention to adopt AI in banking services.

Design/methodology/approach – The qualitative research was carried out using in-depth interviews from officials in the baking industry to understand the importance and challenges of adopting AI in the banking industry. In the quantitative study, a total of 302 completed questionnaires were received from Malaysian banking customers. The data were analysed using the SmartPLS 3.0 software to identify the important predictors of their intention to adopt AI.

Findings – The qualitative results reveal that AI is an essential tool for fraud detection and risk prevention. The absence of regulatory requirements, data privacy and security, and lack of relevant skills and IT infrastructure are significant challenges of AI adoption. The quantitative results indicate that attitude towards AI, perceived usefulness, perceived risk, perceived trust, and subjective norms significantly influence intention to adopt AI in banking services while perceived ease of use and awareness do not. The results also show that attitude towards AI significantly mediates the relationship between perceived usefulness and intention to adopt AI in banking services.

Practical implications – Financial technology (FinTech) is regarded as a critical determinant of strategic planning in the banking industry. While AI provides various disruptive opportunities in the FinTech space in terms of data collection, analysis, safeguarding and streamlining processes, it also poses a sea of threats to incumbent banks. This study provides vital insights for the policymakers of the banking industry to address the challenges of adopting AI in banking. It also provides the important predictors of the bank customers' intention to adopt AI in banking services. Policymakers can devise their strategies to enhance AI adoption considering the facts.

Originality/value – This study is amongst the pioneer in exploring the importance and potential challenges in implementing AI technology in banking services and identifying the essential factors influencing the intention to adopt AI in Malaysia's banking services.

Keywords Artificial intelligence, Bank customers, Intention to adopt, PLS-SEM, Malaysia

Paper type Research paper

1. Introduction

Artificial intelligence (AI) has become omnipresent in transforming all sectors, from manufacturing to retail and service provision (Belanche *et al.*, 2019). AI uses algorithms to

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model intelligent behaviour with minimal human interference (Haenlein and Kaplan, 2019). It remains the most impressive IT application today and has experienced exponential growth over the recent decades (Lee *et al.*, 2018; Wiljer and Hakim, 2019). With a growth rate of approximately 20% per year (International Federation of Robotics, 2017), automated technology can have severe labour displacing effects (Acemoglu and Restrepo, 2020; Baigh *et al.*, 2021). According to Vijai (2019), the technology itself is getting better and smarter day by day, allowing more and newer industries to adopt AI for various applications. International Data Corporation estimates suggest that 75% of business operations will use AI services by 2020 (Crews, 2019).

Likewise, in the banking industry, FinTech is considered an integral determinant of strategic planning (Belanche *et al.*, 2019; Jung *et al.*, 2018). To stay competitive in the marketplace, banks are now seeking AI solutions to replace expensive, tedious, and routine activities (Kaya *et al.*, 2019). AI has thus, become a step-forward game-changer in transforming and digitalising modern businesses. With approximately 11 billion US dollars in 2020 invested in AI, the financial sector is the largest sector contributing to AI (Liu, 2020). According to Alsheibani *et al.* (2018), adopting AI technology tools would enhance the efficiency of the daily operations and thus, boost customer experience. Vijai (2019) noted that the basic AI applications used in banks, such as chat-bots, personalised services, and even AI robots for self-servicing, could generate more efficiency than traditional human advisory services. Such application is demonstrated in some branches of the Bank of Tokyo, where a humanoid robot called Nao attends customers (Marinova *et al.*, 2017) by analysing their emotions from their facial expressions and tone of voice. Unlike its human counterpart, Nao can perform tasks such as 24-h banking and multilingual interaction. With these applications, the Bank of Tokyo has successfully created more time for the branch staff, allowing them to spend more value-added services (Royle *et al.*, 2015).

In line with the fourth industrial revolution globally and National Transformation 2050 (TN50), Malaysia is moving towards AI innovation (Noor and Mansor, 2019). Since the Malaysian government has taken great interest in pursuing AI-enabled technologies, several initiatives have been commenced by agencies such as the Malaysian Digital Economy Corporation (MDEC) (Abdullah *et al.*, 2017). MDEC has announced that it has established an AI unit with local and international experts to support the National AI Framework to ensure Malaysia is on the right track to develop an AI ecosystem in the country. As a result, new technical skills and higher-level capabilities are expected from the current workforce (EAC Focus, 2017). A study from Microsoft stated that by 2021, AI will approximately double the rate of revolution and enhance employee productivity improvements by 60% in Malaysia (Paramasivam, 2019). However, despite having momentum, most Malaysian banks face challenges in adopting AI-induced banking tools (Yun, 2019).

Although the benefits such as cost-effectiveness and better customer service derived from AI applications are well established in the literature (Crosman, 2018), research on AI adoption is very limited. Prior studies in this field have concentrated on techniques and applications (Walczak, 2016), ignoring the customer perspective. While Malaysian customers are prepared to use banking services that rely on AI (Unisys Corporation, 2018), it is still crucial to clearly understand the factors that may influence their decisions. Furthermore, the limited research on AI adoption in banking shows that the implementation stage is still modest (Kaya *et al.*, 2019). The paper, therefore, aims to identify the importance and challenges of AI adoption in banking services from the management perspective and key determinants that drive a wide range of customers towards AI adoption.

To bridge the above research gaps, this study uses both qualitative and quantitative approaches. First, a qualitative research design is employed in the form of a face-to-face interview to explore the importance and the challenges of adopting AI in the banking industry in Malaysia. Given that there is a lack of literature on AI adoption behaviour in

Malaysia, both qualitative and quantitative approaches are well justified. Without proper research on AI adoption, improving the functionality of AI-based systems to facilitate customer engagement will not be possible (Belanche *et al.*, 2019). Moreover, the Malaysian government's initiatives to catapult the progression of AI-enabled technologies (Abdullah *et al.*, 2017) make Malaysia an interesting case for study. Second, extending on the technology acceptance model (TAM), this study examines important factors in investigating consumers' intention to adopt AI (INT) in the banking industry in Malaysia. Since the degree of familiarity with AI varies across customers, as an additional contribution, this study considers knowledge in technology (KT) as a moderating variable relevant to the adoption of AI-driven technology in banking. To harness the full benefits of adopting new technology, it is stated that users' willingness to adopt the system is critical (Davis, 1989; Davis and Venkatesh, 1996). Therefore, the study proposes that the users' attitudes toward AI banking may play a mediating role.

The present study contributes to the existing body of knowledge by providing an exploratory analysis of the customers' viewpoint regarding AI adoption. To keep up with the technological transformation of the banking sector, banks need to better understand the customers' needs to effectively introduce AI. Moreover, this study identifies the key determinants that affect the consumers' decision to adopt AI tools. As an additional contribution, this study examines moderating and mediating relationships to evaluate potential variations in the adoption process depending on customers' characteristics. Lastly, it widens the scope of the AI adoption decision by explicitly incorporating both customers' and bankers' perspectives, which may serve as a good source of information for practitioners while devising AI adoption strategies.

The rest of the paper is organised as follows. The next section presents the literature relevant to the topic of study, incorporating a research framework with a series of hypotheses. Section three describes the methodology adopted. The collected data are then analysed and interpreted before the results are discussed. The final section concludes with the study's implications, limitations, and future directions.

2. Literature review

2.1 Artificial intelligence

AI is intelligence demonstrated by machines with the same critical features as human intelligence. The first General Problem Solver (GPS) was claimed as the original AI due to its ability to imitate human problem-solving skills (Newell and Shaw, 1958). Although computer scientists dealt with a significant shortfall in funding for AI research in the mid-1970s, the period is also known as the AI winter (Ray, 2018); the AI revolution boomed in the first decades of the 21st century. Today, AI is recognised as an intelligent agent system that uses technological devices to autonomously replicate the cognitive abilities of humans to achieve goals (Haenlein and Kaplan, 2019; Wamba-Taguimdje *et al.*, 2020) and improve the possibilities of success in a particular task (Bogue, 2014).

2.2 Impact of artificial intelligence in banking

The concept of FinTech goes beyond e-banking and consumer digitalisation. It focusses on developing and successfully introducing innovative technology instruments to meet users' financial needs and demands (Belanche *et al.*, 2019), such as technological innovation of payments and the automation of lending and borrowing. AI has, therefore, come hand in hand with promises of increases in potential revenue (Park *et al.*, 2016) and greater efficiency gains. Nevertheless, it is important to understand the customer's behaviour to enhance their experience (Schrotenboer, 2019). As a result, banks are now actively investing in AI technology to detect behavioural patterns from customers' experiences. By overcoming the traditional customer service challenges such as assistance in lending decisions and regulatory compliance (Schmelzer, 2019), AI technology tools allow the banks to automatically adjust their offerings and solutions to customers based on their needs (Mallawaarachchi, 2019; Vanneschi *et al.*, 2018).

Furthermore, AI is also being used to create better customer engagement (Nadimpalli, 2017). One of the AI tools that Bank of America is currently using and adopting their customers is the Chatbot service, which aims to provide better customer engagement. The virtual assistants provide 24/7 services to the customer and help banks improve operational efficiency by handling a large volume of inquiries simultaneously (Crosman, 2018). In addition, financial chatbots can guide customers through the complexities of day-to-day cash management, which empowers them to make smarter spending decisions and thus, improve their overall financial health (Abe, 2016).

Moreover, by studying the patterns of data collected from the customers' conversations with chatbots, banks gain unique insights into customers' behaviours and concerns. AI analyses the data and produces meaningful and actionable patterns that can help banks identify previously unknown marketing opportunities, such as reaching out to customers at their most suitable times. Not only that, through the identification of the outliers in a data set, detection of fraud is faster and more cost-effective using AI (Bharadwaj, 2019). However, many barriers exist in introducing service technologies that directly interact with customers (Han and Yang, 2018; Singh *et al.*, 2017). Reconciliation of the data from front to back and data referential are often plagued with quality issues. Hence, having a data quality programme in place is necessary for any large scale AI initiative (Meunier, 2018). Similarly, the success of technology incorporation within service communications depends on the level of engagement between humans and automated technology (Van Doorn *et al.*, 2017). Although banks have a high preference towards FinTech, customers are often unwilling to entrust their money in such AI-driven systems (Belanche *et al.*, 2019; Jung *et al.*, 2018). Therefore, it is crucial to understand customers' viewpoints to ensure that they will benefit from using it for the effective implementation of AI. The current study seeks to close this gap by proposing a model that incorporates the primary factors influencing consumers' intention to adopt AI in the banking industry.

2.3 Theoretical foundation and hypothesis formulation

A research framework is proposed based on the TAM (Davis, 1989; Davis *et al.*, 1989) to further investigate the factors which affect consumers' AI adoption behaviour. Since TAM can predict user acceptance of information technology to a great extent, it is considered as one of the best models to investigate users' reactions to technological innovations within the field of information systems (Alalwan *et al.*, 2016; Belanche *et al.*, 2019; Davis, 1989; Salimon *et al.*, 2017). TAM has been one of the most adopted models in the last two decades (Alalwan *et al.*, 2016) to depict the customers' intention to adopt various electronic banking services such as telebanking (Curran and Meuter, 2007) or Internet banking (Salimon *et al.*, 2017).

Built upon the theory of reasoned action (TRA) (Fishbein and Ajzen, 1975), TAM indicates whether casual relationships exist amongst perceived usefulness (PU), perceived ease of use (PEOU), the user's attitudes and intentions (Davis *et al.*, 1989). TAM explains the information technology adoption behaviour through two primary variables, PEOU and PU (Davis, 1989). However, it has been often criticised that the simplicity of TAM prevents it from depicting a holistic picture of users' technology adoption behaviour (Alalwan *et al.*, 2016). To shed light on the above criticism about the use of TAM to understand individuals' intention, six bank officers were asked to identify potential factors related to customers' INT in banking services in Malaysia. Based on their feedback, this study identifies the factors presented in Table 1.

Next, an extensive literature review was conducted to find the existing and/or potential relationship between the factors (Table 1) and customers' intention behaviour. Prior studies noted that factors used in TAM (i.e. PEOU and PU) and additional factors such as awareness (AW) (Albaity and Rahman, 2019; Mutahar *et al.*, 2018), perceived risk (PR) (Alalwan *et al.*, 2016; Hanafizadeh *et al.*, 2014a, b; Riquelme and Rios, 2010), perceived trust (PT) (Alalwan *et al.*, 2016; Payne *et al.*, 2018; Susanto *et al.*, 2016; Zhou, 2011) and subjective norms (SN) (Belanche *et al.*, 2019; Fishbein and Ajzen, 1975; Venkatesh and Davis, 2000) are potential predictors of customers' intention behaviour. Therefore, this study used the extended version of TAM by incorporating additional factors such as AW, PR, PT and SN .

2.3.1 Technology acceptance model (TAM) and related hypotheses. Extending on TAM, this study attempts to describe the factors that significantly affect the customers' INT in banking. The TAM hypothesises that the main determinants of users' attitude towards technology are users' PU and PEOU. In turn, in concordance to the cost-benefit paradigm, users' attitude affects their behavioural intentions to adopt the technology (Alzubi *et al.*, 2017; Ghazizadeh *et al.*, 2012). Attitude reflects a person's mental state to respond either favourably or unfavourably to a particular behaviour, such as adopting new technology (Alsajjan and Dennis, 2010; O'cass and Fenech, 2003). Since Internet banking allows customers to have a wide array of choices, the significance of attitude in predicting consumer behaviour has more relevance than ever before (Alsajjan and Dennis, 2010). No previous generation as digital natives today have been more accepting of technology in their everyday lives (Smith and Nichols, 2015). As a result, they tend to engage more independently in processing real-time data related to their financial transactions (Payne *et al.*, 2018).

According to Davis (1989), perceived ease is the extent to which a person perceives that it would be effort-free to use a particular technology. In contrast, PU is the degree to which a person believes that his or her performance would be better using a particular technology. Many empirical studies on electronic banking have acknowledged PU as a significant antecedent of users' intention to adopt the technology (Mutahar *et al.*, 2018; Salimon *et al.*, 2017). High PU amongst users leads to the continuance of positive use–performance relationship (Davis, 1989). Hence, electronic bank users prefer to endorse technology (Jahangir and Begum, 2008) that has intrinsic advantages such as banking service mobility, cost and time effectiveness and privacy of banking operations (Yee-Loong Chong *et al.*, 2010; Devi Juwaheer *et al.*, 2012; Salimon *et al.*, 2017). Similarly, extensive research documents the significant effect of PEOU on usage intention (Belanche *et al.*, 2019; Jahangir and Begum, 2008; Mutahar *et al.*, 2018; Salimon *et al.*, 2017). Users are more likely to feel favourable towards a technology and accept it when the system is perceived to be easier to use (Davis, 1989). Therefore, the following hypotheses are proposed:

H1. PEOU has a positive effect on attitude towards AI (ATT) in banking.

Table 1. Factors identified by interviewees

Interviewee	Attitude	Awareness	Usefulness	Ease of use	Risk	Trust	Knowledge in technology	Subjective norms
1	√	√	√			√		
2	√	√		√	√			
3	√	√	√	√	√	√	√	√
4	√	√	√	√		√		√
5	√	√			√	√		
6	√	√			√			√
Total	6	6	3	3	4	4	1	3

Source(s): Authors' processing

H2. PU has a positive effect on ATT in banking.

H3. ATT in banking has a positive effect on INT in banking.

H4. PEOU has a positive effect on INT in banking.

H5. PU has a positive effect on INT in banking.

2.3.2 Awareness and intention. This study defines AW as the user's level of knowledge about AI in banking. Sathye (1999) revealed that low AW of online banking is one of the critical factors that affect customers' not to adopt online banking. This is because customers are not aware of the advantage and disadvantages of the online banking system. Likewise, the low level of acceptance and adoption of mobile banking services lacks AW of the benefits of using the services (Alzubi *et al.*, 2017; Mutahar *et al.*, 2018; Sathye, 1999). Charbaji and Mikdashi (2003) found that AW significantly influenced the behavioural intention to use e-government services amongst Lebanese postgraduate students. Similarly, results were found for Pakistan citizens' intention to use e-Government services or obtain information or perform a transaction using the government website (Rehman *et al.*, 2012). Thus, the following hypothesis is proposed:

H6. AW has a positive effect on INT in banking.

2.3.3 Perceived risk and intention. The theory of PR tends to examine the behaviour of customers and identify factors that affect their decision-making process (Taylor, 1974). Although the definition of PR has changed due to technological advancements, in general, PR is conceptualised as the consumer's subjective expectation of suffering a loss in pursuit of the desired outcome (Pavlou, 2001). In terms of AI, PR can be defined as the probability of loss in the quest of obtaining a preferred outcome while using AI technology. According to Martins *et al.* (2014), PR and trust are pervasive concepts that influence the behavioural intentions to use Internet banking. Bauer (1967) highlighted that consumers evaluate the PR of the products and services when they intend to purchase and/or adopt them either consciously or unconsciously. However, as posited by Howcroft *et al.* (2002), the clients are concerned about mobile banking usage. They are often anxious about privacy and the security of their financial information. In the context of Malaysia, most of the consumers are willing to support data sharing in an open banking environment, but only if privacy and security concerns are addressed (Malay Mail, 2018). Hence, the following hypothesis is proposed:

H7. PR has a negative effect on INT in banking.

2.3.4 Perceived trust and intention. Multifaceted and dynamic construct, PT is the most reflective in the context of uncertain and risky environments (McKnight *et al.*, 2002; Payne *et al.*, 2018). Regarding e-investors, PT is one of the variables that lead them to believe that online financial dealers can provide them with the services offered (Roca *et al.*, 2009). Fragata and Moustakas (2013) stated that maintaining transaction trust is crucial for attracting and retaining bank customers. Likewise, Gefen *et al.* (2003) stated that trust is expected to immediately affect the customers' intention to adopt mobile banking and could implicitly influence behavioural intention via enabling the role of performance expectancy. Faqih (2016) found that when customers have a higher level of trust in the technology, they are more likely to adopt the new service. If there is a lack of trust, customers may decline to provide their personal information to the banks involved in the transaction. Customers' assessment of trust about security mitigates uncertainty, which consequently stimulates acceptance (Zhou, 2011). The literature above shows that PT is an important determinant in the adoption of AI technology. Therefore, the following hypothesis is developed:

H8. PT has a positive effect on INT in banking.

2.3.5 Subjective norms and intention. In social psychology, SN is defined as the belief that an important person or group of people will approve and support a particular behaviour (Fishbein and Ajzen, 1975). According to Taylor and Todd (1995), social influences are comparable to SN and, it is defined as an influence and opinion from other people. This view agrees with previous research on technology-based innovations, specifically in the spectrum of e-finance (Belanche *et al.*, 2019). According to Bhattacherjee (2000), interpersonal (superiors and peers) and external sources (mass media news) are the primary contributors to SN. Given that social influence plays a critical role in determining the acceptance and usage behaviour of adopters of new information technology (Venkatesh and Morris, 2000), this study proposes the following hypothesis:

H9. SN has a positive effect on INT in banking.

2.3.6 Mediating effects: attitude towards AI. Users' attitude towards a system reflects a user's evaluation (positive or negative) about adopting the system (Shanmugam *et al.*, 2014). Ajzen and Fishbein (1980) suggested that attitude is the level of trust a person must recognise with the effects that the approval of behaviour will offer an assessment of the conceivable results. It has been stated that it is critical to have an attitude towards and acceptance of new technology because it impacts the success of information system adoption. If the user is unwilling to adopt the system, it does not benefit the organisation (Davis, 1989). The influence of the construct attitude on the evolution of new technology is well documented in past studies (O'cass and Fenech, 2003; Shanmugam *et al.*, 2014; Suki and Suki, 2011). While users' perception of use can significantly affect their willingness to utilise a certain technology (Elhajjar and Ouaida, 2020; Hanafizadeh *et al.*, 2014a, b), the opposite relationship is also true. According to Jahangir and Begum (2008), the users' attitude towards technology can affect their perception of use and, thus, influence their intention to adopt the technology. The same relationship may hold in terms of AI adoption in the banking industry. Thus, the following hypotheses are proposed:

H10. ATT in banking mediates the relationship between PEOU and INT in banking.

H11. ATT in banking mediates the relationship between PU and INT in banking.

2.3.7 Moderating effects: knowledge in technology. The influence of technological breakthroughs in the spectrum of finance brought forward by AI is not limited to the firms only; the customers are also affected (Singh *et al.*, 2017). The recent trend in the banking industry suggests that customers are paying more attention to adopting AI-based technology (Belanche *et al.*, 2019). Although growing popularity for programming courses and materials for AI systems are observed, not all individuals who opt for AI services possess the same level of knowledge about such innovations (Young *et al.*, 2009). Therefore, to better understand the adoption process, this study proposes KT as the moderator that impact users' INT in the banking industry. According to An (2007), knowledge is a moderator in explaining the usage of information in decision-making procedures and behaviour. While Curran and Meuter (2005) suggest that the consumers' PEOU of online self-service is greater when they have more knowledge about the technology, the findings of Castañeda *et al.* (2007) posits that having a higher level of familiarity with technology makes the customers value the innovation more (Yang *et al.*, 2009) in terms of usefulness, AW and attitude. Additionally, as users become more familiar with the technology, they tend to perceive lower risk and higher trust in the bank's competency, which creates a favourable effect on their technology adoption decision (Payne *et al.*, 2018). Conversely, when users have greater familiarity with technology, they will be less affected by SN (Belanche *et al.*, 2019) because they will have their knowledge to guide them in their decision-making process. Thus, the following hypotheses are proposed:

H12. The positive relationship between PEOU and INT in banking will be stronger for higher level of KT .

H13. The positive relationship between PU and INT in banking will be stronger for higher level of KT .

H14. The positive relationship between AW and INT in banking will be stronger for higher level of KT .

H15. The negative relationship between PR and INT in banking will be weaker for higher level of KT .

H16. The positive relationship between PT and INT in banking will be stronger for higher level of KT .

H17. The positive relationship between SN and INT in banking will be weaker for higher level of KT .

3. Research design

3.1 Qualitative method

A semi-structured face-to-face interview technique was adopted to gather data from bank officers. Respondents were asked about the importance and challenges of adopting AI in the banking sector. The interviewees include experienced bankers at managerial level and above, IT professionals and analysts. A summary of the respondents is listed in Table 2. The study assured that respondents' identity (such as respondents' names, bank's profiles) would be kept anonymous, and collected data will be used only for academic purposes. The interviewees were targeted based on their engagement with their respective banks (Table 2). A total of six out of 10 participants agreed to participate in the interview. Finally, six semi-structured interviews were conducted and analysed using an open and axial coding approach (Strauss and Corbin, 1990). Each interview took between 40 and 60 min to complete. All the interviews were conducted face-to-face at the workplace of respondents. The questions were prepared by looking at previous literature during the semi-structured interview (Rahman *et al.*, 2020). The interview questions were validated using a commentary by academicians. The list of interview questions is presented in Table A1.

3.2 Quantitative method

3.2.1 Sample and data collection. A self-administrated structured questionnaire was used to obtain the data needed. The target respondents include those clients who have experience in banking transactions with Internet or mobile banking system. We followed the purposive sampling technique to select desired respondents for data collection. Hence, a screening

No	Bank	Individual	Respondents' position
1	A	Interviewee 1	General manager
2	B	Interviewee 2	Deputy General manager
3	C	Interviewee 3	Head of operations and services
4	D	Interviewee 4	Branch manager
5	E	Interviewee 5	Head of IT security operations
6	F	Interviewee 6	Head of research and development

Source(s): Authors' processing

Table 2. Summary of respondents

question was included in the questionnaire stating whether they have at least six months of the Internet or mobile banking experience with their banks. Those who answered with "yes" – was retained for data analysis. The survey questionnaires were distributed through social media platforms such as Facebook, WhatsApp, WeChat, etc. DIGFIN (2020) reported that about 92% of the adult population in Malaysia have a bank account. Moreover, Malaysia recorded a remarkable increase in mobile banking subscribers, which stood at 33.6 million users in July 2020 (Goh, 2020). This statistic indicates that Internet or mobile banking are getting acceptance amongst Malaysian consumers who use social media platforms such as Facebook, WhatsApp, WeChat, Twitter etc. Hence, it is reasonable to conduct a survey using social media platforms. A total of 357 questionnaires were returned during the survey. Out of these 357 questionnaires, we retained 302 useable responses after discarding the participants who had no Internet banking experience with their banks in the last six months (32 responses) and missing responses (23 responses). Based on the sample size requirements in structural equation modelling (SEM) using G*Power analysis (Ringle *et al.*, 2015a), it was estimated that the minimum sample required to analyse the proposed model is 194. Hence, the useable response of 302 was sufficient to meet the statistical power of 80% (Chin and Newsted, 1999).

The research framework in Figure 1 illustrates the direct and indirect effect of selected variables on the INT in banking services. It also includes the moderating effects of KT . There are seven direct effects, two indirect effects and six moderating effects on AI intention in the model, which are presented using the following equations:

$$\mathrm{INT}_i = \alpha_0 + \alpha_1\,\mathrm{PEOU}_i + \alpha_2\,\mathrm{PU}_i + \alpha_3\,\mathrm{AW}_i + \alpha_3\,\mathrm{PR}_i + \alpha_4\,\mathrm{PT}_i + \alpha_5\,\mathrm{SN}_i + \alpha_6\,\mathrm{ATT}_i + \varepsilon_i \tag{1}$$

$$\mathrm{ATT}_i = \beta_0 + \beta_1\mathrm{PEOU}_i + \beta_2\,\mathrm{PU}_i + u_i \tag{2}$$

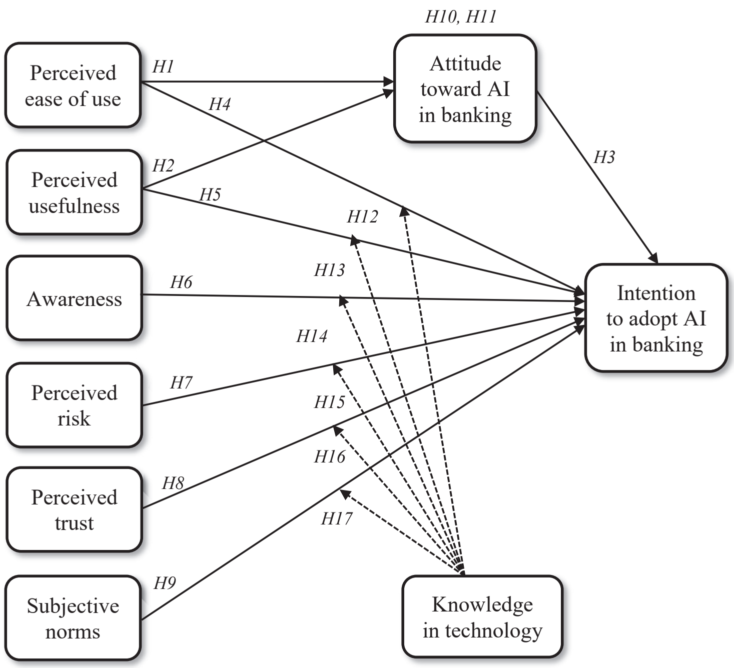

Figure 1.
Research framework

$$\mathrm{INT}_i = \beta_0 + \beta_{1*}\alpha_6\,\mathrm{PEOU}_i + \beta_{2*}\alpha_6\,\mathrm{PU}_i + u_i \tag{3}$$

$$\begin{aligned}\mathrm{INT}_i = {} & \gamma_0 + \gamma_1\,\mathrm{PEOU}_i + \gamma_2\,\mathrm{PU}_i + \gamma_3\,\mathrm{AW}_i + \gamma_3\,\mathrm{PR}_i + \gamma_4\,\mathrm{PT}_i + \gamma_5\,SN_i \\ & + \gamma_6\,\mathrm{PEOU}\times\mathrm{KT}_i + \gamma_7\,\mathrm{PU}\times\mathrm{KT}_i + \gamma_8\,\mathrm{AW}\times\mathrm{KT}_i + \gamma_9\,\mathrm{PR}\times\mathrm{KT}_i + \gamma_{10}\,\mathrm{PT}\times\mathrm{KT}_i + \gamma_{11}\,\mathrm{SN}\times\mathrm{KT}_i + v_i\end{aligned} \tag{4}$$

Note: INT is the customer intention to adopt AI in banking, PEOU is perceived ease of use, PU is perceived usefulness, AW is awareness, PR is perceived risk, PT is perceived trust, SN is subjective norms, ATT is attitude toward AI in Banking, KT is knowledge in technology, $\alpha_0 - \alpha_6$, $\beta_0 - \beta_2$, $\gamma_6 - \gamma_{11}$ are the coefficients for the direct, indirect and moderating effects.

Equation (1) shows the direct relationships between independent variables and the INT in banking. Equation (2) presents the indirect effect of the two independent variables (PEOU and PU) of INT in banking through the ATT in banking. Equation (3) shows whether the direct relationships between independent variables and the INT in banking will be stronger or weaker when KT is high.

This study applied the SEM techniques to estimate the path coefficients hypothesised in Figure 1. As the research model is highly complex (i.e. more than 6 constructs) and the statistical objective is prediction-oriented, the partial least squares structural equation modelling (PLS-SEM) method compared to co-variance-based structural equation modelling (CB-SEM) is more suitable for this study (Hair *et al.*, 2017a). Besides, PLS-SEM also handles both normal and non-normal data distribution. Therefore, this study analysed the proposed research model based on PLS-SEM techniques using SmartPLS 3.3.2 version (Ringle *et al.*, 2015b). Moreover, SPSS v23 was used to estimate the descriptive statistics and common method bias (CMB).

3.2.2 Measurement and constructs. All the study constructs were measured using previously validated scales adapted from past research. AW about technology in banking services was measured using a 4-items scale adapted from Al-Somali *et al.* (2009) and Rehman *et al.* (2012). Likewise, PEOU (4-items), PU (4-items), SN (4-items), attitudes towards AI (3-items), and INT (3-items) were adapted from Belanche *et al.* (2019). PR was measured using a 4-items scale adapted from Alalwan *et al.* (2016) and Featherman and Pavlou (2003). Finally, the 4-items scale in Payne *et al.* (2018), Susanto *et al.* (2016) and 3-items scale in Lin and Filieri (2015) were used to measure PT and KT , respectively. These items were anchored using a 7-point Likert scale ranging from 1 = strongly disagree to 7 = strongly agree. Before conducting the survey, we distributed the questionnaire amongst five academic experts to assess the face validity of measurement scales. By incorporating a few minor changes (i.e. the wording of a few statements) in the questionnaire, a pilot study with 50 participants was carried out to check the reliability of the scales. The Cronbach's alphas of all constructs resulting from the pilot study were above 0.7, indicating an acceptable construct reliability level. We also revised a few statements in the questionnaire based on the feedback received from the participants and carried out the final survey.

4. Results and analysis

4.1 Results from qualitative data analysis

4.1.1 Importance of AI in banking. Concerning the broad theme of, importance of AI in banking, three sub-themes emerged: fraud detection and risk prevention analytics, prediction of outcome and customer experience. The emergence of these sub-themes from the interview explains that AI in banking facilitates detection of any fraudulent activities, violation of any security controls, etc. The significance of AI as a tool for fraud detection and risk prevention analytics coincided with that of González-Carrasco *et al.* (2019). They stated that machine learning and big data technologies could help banks overcome problem such as money laundering and mortgage fraud issues. According to interviewee 4,

> AI analytic tool on fraud detection and risk prevention would help in a bank's back end operations such as reducing the time in investigating fraud cases . . . thus increase effectiveness

However, according to KPMG's Global Banking Fraud Survey, banks are still reactive towards fraud and are not investing enough in fraud risk management (KPMG International, 2019). Similarly, the interviewees agreed that AI-based technology helps banks make accurate predictions about customers' behaviour by observing their past data patterns. This allows the banks to promote and market the right product to the right customer at the right time on social media platforms. Thus, bank management can manage customer experience or satisfaction more effective way than before. Payne *et al.* (2018) stated that AI services in mobile banking will offer customers a more customised banking experience. However, the implementation of AI in banking comes hand in hand with several challenges. As pointed out by Interviewee 5,

> Due to [. . .] advanced technology [. . .] people are very creatively finding new ways to break rules and create fraud

4.1.2 Challenges of implementation of AI in banking. Although the use of AI in the banking industry has become a trendsetter, the journey of AI adoption in the banking industry is still far from moving (Alzaidi, 2018). From the interviews, it was found that to more effectively adapt the framework for AI in banking, it was necessary to ensure that AI banking was in place within the regulatory requirements. The current regulatory framework in Malaysia does not incorporate AI tools. As stated by Interviewee 1,

> [. . .] yet to have a clear guidance [. . .]

No guidelines in terms of AI adoption are provided by the central bank of Malaysia, Bank Negara. As a result, banks in Malaysia do not proactively take steps towards AI implementation. In addition to that, the interviewees agreed that the risk of data privacy and security issue acts as another hindrance to AI implementation. Interviewee 5 stated,

> [. . .] customer data protection issue arises when the customers have no idea of their data being used to promote or advertise certain products [. . .]

Han and Yang (2018) indicated that security or privacy-related issues are potential problems with the abundance of devices and services based on AI . Therefore, corporate communication units should make suitable promotional and marketing programmes for increasing customer trust levels. However, having a trustworthy system can also be a challenge. While interviewee 3 outlined the negative consequences of AI-based systems,

> [. . .] possibility of having a wrong decision or the system could be hacked and eventually have the wrong outcome [. . .]

Interviewee 6 suggested,

> [. . .] when the AI technology is lifted up the level like real human [. . .] AI would become more trustworthy

According to Belanche *et al.* (2019), customers are generally afraid to entrust their money in AI-driven systems, despite banks' strong preference for FinTech. Jo Bitner (2001) further postulated that if technologies and services are dependable and trustworthy, consumers are willing to adjust because of their benefits. However, the interviewees pointed out that the barriers to AI adoption may persist due to the lack of relevant skills and compatibility issues with the current IT infrastructure. Interviewees 4 and 6 specified that,

> [. . .] to migrate to AI system, it would require longer time [. . .] as the AI technology is still yet to mature [. . .]

Moreover, the existing IT infrastructure of the bank may not be compatible with newer technologies. At the current state, for instance, in processing a customer loan application, human intervention is required. Similarly, interview data showed that employees' lack of data analytics skills makes it difficult for banks to adopt AI technology. According to Interviewee 5 and 6,

> [. . .] not many employees have the skill to run data analytics and interpret the result correctly [. . .]

The arrival of new technologies has significantly changed the requirement for skills beyond the technology sector (Berger and Frey, 2016).

4.1.3 Confirming important factors affecting adoption of AI in banking. According to the interviewees, consumers' AW about the AI system is considered the most significant factor, followed by trust, usefulness, ease of use, risk, SN and KT . According to Interviewee 3,

> [. . .] the majority of Malaysian has low AW of AI in banking [. . ..]

Interviewee 5 noted that,

> Customers do not know whether the services are from AI technologies. Customers will only think that the bank is getting smarter as the banks meet their needs better

In line with past literature (Charbaji and Mikdashi, 2003; Rehman *et al.*, 2012), the interview findings advocate that AW is essential for influencing consumers' INT ; especially because some users may have comfort issues with AI-based transactions. Interviewee 4 noted that,

> [. . .] some customers prefer to deal with the human staff; therefore, customers might find it uncomfortable if they are aware that there is a robotic AI tool behind to serve them [. . .]

A consensus was found between interviewees 3, 4 and 5 that some customers may experience difficulties trusting AI-induced services mostly because there is no control set in place to verify that the AI induced transactions are accurate.

> A customer might fear to accept AI in banking services [. . .] do not provide accurate results [. . .]

> [. . .] the customer has done an automated transaction. How do they know the technology work and ensure the transaction is happening . . .

The trust issues that customers experience are further reinforced by the risks associated with AI technology. The interviewees pointed out that a technology-based system is prone to technological risks such as data hacking and system failure. To minimise the trust issues of customers, special attention must be given to customer privacy and customer data protection. For instance, using predictive analysis tools, a bank sales officer may offer a customer a customised loan scheme by analysing the customer's payment history. Some customers may not like that the banks have so much access to their personal information and therefore may consider AI tools a risk to their privacy. As stated by Interviewee 5,

> [. . .] customer could be shocked as how the bank sales officer knows so much about my private information [. . .]

While the factors usefulness SN subjective norms were well agreed to influence the consumers' INT in the banking sector, the interviewees stressed the role of customers' age in establishing the relationship between consumers' INT and ease of use, and KT , respectively. According to Interviewee 3,

> [. . .] younger generation [. . .] would find it easy to use the AI compared to the older generation [. . .]

> [. . ..] younger generations may easily adopt AI, but for the older age group they would still prefer to go the branch [. . .]

Overall, the findings indicate that AI can address fraud detection and risk prevention in banking services. The findings also suggest that the major challenges related to AI adoption are the absence of regulatory requirements, data privacy and security, and a lack of relevant skills and IT infrastructure.

4.2 Results from quantitative data analysis

4.2.1 Profile of respondents. Table 3 highlights the demographic profile of the respondents. Females were more willing to participate than males, with 57.6% females and 42.4% males. The majority of the respondents belong to the Chinese (62.60%) ethnic group and are between 26 and 45 years old. A total of 85.8% of the respondents attained either Diploma or Bachelor degree. Approximately 91% of respondents are employed, of which about 31% have experience working in the banking and finance industry. Thus, their responses would be very much relevant to this study setting.

4.2.2 Common method bias (CMB). This study accounts for the assessment of CMB which is considered an important concern in the survey research (Podsakoff *et al.*, 2003). We examined CMB using latent variable correlation matrix procedure as recommended in Bagozzi and Yi (1990). According to this method, a correlation value exceeding 0.90 indicates the presence of CMB. The findings in Table 4 exhibits that the highest correlation value was 0.83 between ATT and INT. Although this score is close to 0.90 but clearly below the threshold level, suggesting CMB is not a concern (Pavlou *et al.*, 2007). Moreover, Harman's single factor test was employed using SPSS v23 to estimate the variance of the first factor. Results showed that the first factor without rotation accounted for 47.10% of the variance, which is lower than the cut-off value of 50%. This procedure further supports that CMB is not a concern in this study (Chuah *et al.*, 2018; Sarker *et al.*, 2021).

4.2.3 Measurement model analysis. The proposed model was analysed for reliability and validity based on the standard criteria recommended by Hair *et al.* (2017b). As all measurement models of the research framework are reflective, the internal consistency reliability and convergent validity were examined based on composite reliability (CR), Cronbach's alpha (CA), factor loading and average variance extracted (AVE). "*Reflective measurement models are composite latent constructs whose indicators (measured variables) are assumed to be influenced, affected, or caused by the underlying latent variable*" (Hair *et al.*, 2020, p. 104). The results in Table 5 show that the reliability of all reflectively measured constructs is at a satisfactory level as the CR and CA values of corresponding constructs were above the benchmark value of 0.70. Sarstedt *et al.* (2017) postulated that convergent validity is achieved when the factor loading of reflective items and AVE exceed 0.708 and 0.50, respectively. The findings demonstrate that the factor loading of all reflective items exceeded 0.708, except for the AW4 (loading = 0.069). Due to the low outer loading of 0.069, AW4 was discarded. Moreover, the AVEs of constructs ranged from 0.732 to 0.922. As the results of both factor loading and AVE of reflective constructs met the benchmark values advocated in Hair *et al.* (2017b), the convergent validity of measurement models is achieved. The items of all the variables are presented in Table A2.

Next, the discriminant validity of study constructs was investigated using both Fornell–Larcker (FL) and Heterotrait–Monotrait (HTMT) ratio of correlations criteria. According to the FL criterion, discriminant validity of the latent construct is achieved when the square root of each construct's AVE (i.e. the diagonal value of the table) is higher than the corresponding row and column values of correlation (Fornell and Larcker, 1981). Recent advancement in SEM methods indicates that the HTMT criterion is more rigourous when investigating discriminate validity (Henseler *et al.*, 2015). Based on the HTMT criterion, a correlation value of the two constructs should be lower than either 0.85 or 0.90 to achieve discriminant validity. However, the choice of cut-off values should not

Questions	Category	f	%	Questions	Category	f	%
Age	18–25 years old	30	9.90	Working industry	Banking and finance	94	31.10
	26–45 years old	238	78.80		Information technology	51	16.90
	46–60 years old	34	11.30		Oil and gas/ Manufacturing/ Engineering	56	18.50
					Wholesale/Retail trade	16	5.30
					Healthcare/ Pharmaceutical	21	7.00
					Construction	7	2.30
					Education	8	2.60
					Others/Self-employed	49	16.20
Gender	Male	128	42.40	Job position	Junior staff	46	15.20
	Female	174	57.60		Senior staff	112	37.10
					Lower-level manager	38	12.60
					Middle-level manager	57	18.90
					Senior-level manager	23	7.30
					Housewife	7	2.30
					Others/Self-employed	19	6.30
Race	Malay	87	28.80	Income level (RM)	0–2,499	22	7.30
	Chinese	189	62.60		2,500–4,999	77	25.50
	Indian	20	6.60		5,000–7,499	88	29.10
	Bumiputera sabah and sarawak	3	1.00		7,500–9,999	47	15.60
	Others	3	1.00		10,000–15,000	16	5.30
					>15,000	14	4.60
					No response	38	12.60
Marital	Single	149	49.30				
	Married	138	45.70				
	Divorced/Widowed	15	5.00				
Religion	Islam	93	30.80				
	Christian	53	17.50				
	Hindu	11	3.60				
	Buddhist	123	40.70				
	Others	22	7.30				
Region	North	31	10.30				
	Central	205	67.90				
	South	33	10.90				
	East coast	6	2.00				
	East Malaysia	27	8.90				
Education	High school	9	3.00				
	Diploma	46	15.20				
	Bachelor's degree	213	70.50				
	Master's degree	31	10.30				
	Doctoral degree	3	1.00				

Note(s): *f* = Frequency

Table 3. Demographic profile

be heuristic (Franke and Sarstedt, 2019). Due to the conceptual similarity in defining attitude and intention, this study chose 0.90 as HTMT cut-off value. The results in Table 6 demonstrate that none of the square roots of each construct's AVE is lower than the corresponding row and column values. Besides, all HTMT values are below 0.90, indicating discriminant validity is assured.

4.2.4 Structural model assessment. The structural model assessment begins by checking the variance inflation factor (VIF) scores of endogenous variables. Results show that the VIF

Constructs	ATT	AW	INT	KT	PEOU	PR	PT	PU	SN
ATT	1								
AW	0.46	1							
INT	0.83	0.48	1						
KT	0.46	0.41	0.46	1					
PEOU	0.60	0.57	0.61	0.57	1				
PR	0.18	0.24	0.13	0.17	0.20	1			
PT	0.74	0.51	0.73	0.45	0.65	0.12	1		
PU	0.74	0.50	0.72	0.46	0.80	0.20	0.68	1	
SN	0.58	0.38	0.61	0.40	0.47	0.29	0.62	0.57	1

Note(s): ATT = Attitude towards AI in banking, AW = Awareness, INT = Intention to adopt AI in banking, KT = Knowledge in technology, PEOU = Perceived ease of use, PR = Perceived Risk, PT = Perceived trust, PU = Perceived usefulness, SN = Subjective norms

Table 4.
Latent variable correlation results

Constructs	Items	Loadings	Mean	Std. dev	CA	CR	AVE
Attitude towards AI in banking	ATT1	0.946	4.889	1.169	0.948	0.967	0.906
	ATT2	0.956					
	ATT3	0.954					
Awareness	AW1	0.954	4.103	1.415	0.958	0.973	0.922
	AW2	0.966					
	AW3	0.961					
	*AW4**	*0.069*					
Intention to adopt AI in banking	INT1	0.949	4.733	1.186	0.900	0.938	0.834
	INT2	0.941					
	INT3	0.846					
Knowledge in technology	KT1	0.940	5.243	1.304	0.935	0.959	0.886
	KT2	0.930					
	KT3	0.953					
Perceived ease of use	PEOU1	0.882	4.784	1.249	0.932	0.952	0.831
	PEOU2	0.943					
	PEOU3	0.920					
	PEOU4	0.901					
Perceived risk	PR1	0.950	4.681	1.268	0.933	0.948	0.822
	PR2	0.951					
	PR3	0.933					
	PR4	0.781					
Perceived trust	PT1	0.852	4.622	1.161	0.930	0.950	0.827
	PT2	0.932					
	PT3	0.933					
	PT4	0.917					
Perceived usefulness	PU1	0.959	4.909	1.294	0.972	0.979	0.922
	PU2	0.969					
	PU3	0.972					
	PU4	0.939					
Subjective norms	SN1	0.825	4.722	1.159	0.878	0.916	0.732
	SN2	0.866					
	SN3	0.853					
	SN4	0.877					

Note(s): *AW4 was deleted due to poor factor loading; CA = Cronbach's Alpha; CR = Composite Reliability; AVE = Average Variance Extracted

Table 5.
Reliability and convergent validity for the measurement model

Fornell–Larcker criterion	ATT	AW	INT	KT	PEOU	PR	PT	PU	SN
ATT	*0.952*								
AW	0.459	*0.960*							
INT	0.826	0.479	*0.913*						
KT	0.458	0.405	0.455	*0.941*					
PEOU	0.600	0.571	0.614	0.567	*0.912*				
PR	0.179	0.239	0.127	0.174	0.195	*0.906*			
PT	0.736	0.510	0.733	0.450	0.646	0.115	*0.909*		
PU	0.736	0.495	0.720	0.462	0.799	0.201	0.684	*0.960*	
SN	0.584	0.379	0.611	0.400	0.469	0.294	0.623	0.572	*0.855*

Note(s): Diagonal values (italic) are the square root of the AVE, while the off-diagonals are correlations

HTMT criterion	ATT	AW	INT	KT	PEOU	PR	PT	PU	SN
ATT									
AW	0.480								
INT	0.884	0.514							
KT	0.484	0.427	0.493						
PEOU	0.636	0.604	0.666	0.607					
PR	0.171	0.253	0.118	0.184	0.189				
PT	0.781	0.540	0.793	0.481	0.690	0.116			
PU	0.766	0.513	0.766	0.483	0.840	0.187	0.717		
SN	0.639	0.409	0.680	0.439	0.516	0.332	0.692	0.619	

Note(s): ATT = Attitude toward AI in Banking, AW = Awareness, INT = Intention to adopt AI in Banking, KT = Knowledge in Technology, PEOU = Perceived ease of use, PR = Perceived Risk, PT = Perceived Trust, PU = Perceived Usefulness, SN = Subjective Norms

Table 6. Discriminant validity

scores for two endogenous variables of this study (i.e. ATT and INT) were lower than 5 (i.e. VIF values ranged from 1.16 to 4.08), indicating no concern for multicollinearity (Hair *et al.*, 2017b). Next, the research model was evaluated for model fit using the standardised root mean square residual (SRMR) (Henseler *et al.*, 2016). An SRMR value of 0.058, below the threshold level of 0.08, demonstrated that the research model has a good model fit (see Figure 2).

The research model consists of a total of 17 hypotheses. This study followed 5,000 bootstrapping subsamples techniques to examine the significance of hypotheses testing (Hair *et al.*, 2017b; Sarstedt *et al.*, 2017). The results in Table 7 exhibit that between the two antecedents (PEOU and PU), PU had a large positive significant effect ($\beta = 0.711$) on ATT in banking . Also, the 95% bias-corrected confidence interval (95% CI) [0.58, 0.83] did not contain a "0" between the lower and upper limit, signposting a significant relationship. Whereas, the relationship of PEOU → ATT was insignificant, as 95% CI containing a "0" (−0.10, 0.17). Hence, H2 is supported, but H1 is not. Next, the effect of ATT in banking , PEOU, PU, AW, PR, PT and SN on the INT in banking were examined. Amongst the seven direct path relationships, the effect of ATT on INT was the highest and positively significant ($\beta = 0.518$), followed by PT → INT ($\beta = 0.143$), PU → INT ($\beta = 0.133$), SN → INT ($\beta = 0.131$). In contrast, the influence of PR on INT was negative but significant

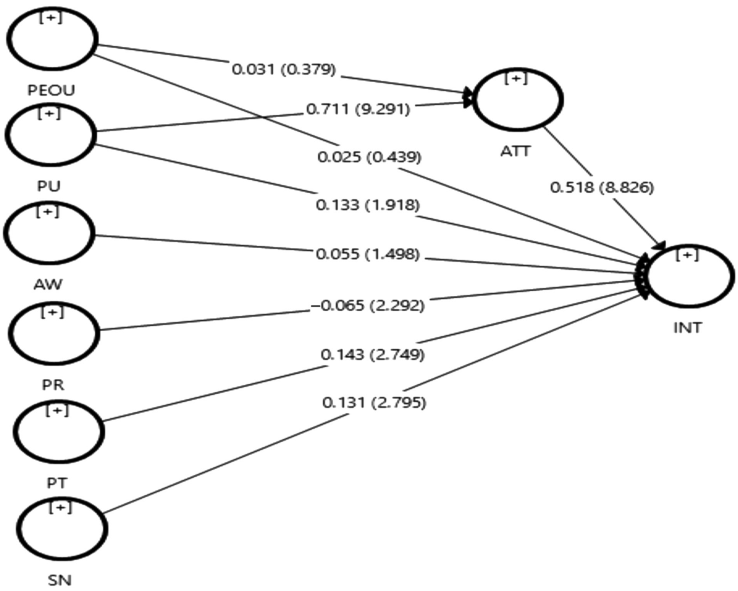

Figure 2.
Structural model

Table 7.
Structural model analysis

Hypotheses		Std. Beta	SE	t-value	95% CI	Decision	Effect size
H1	PEOU → ATT	0.031	0.08	0.38	[−0.10, 0.17]	NS	0.001
H2	PU → ATT	0.711**	0.08	9.29	[0.58, 0.83]	S	0.399
H3	ATT → INT	0.518**	0.06	8.83	[0.42, 0.61]	S	0.359
H4	PEOU → INT	0.025	0.06	0.44	[-0.07, 0.12]	NS	0.001
H5	PU → INT	0.133*	0.07	1.92	[0.02, 0.25]	S	0.017
H6	AW → INT	0.055	0.04	1.50	[0.00, 0.12]	NS	0.007
H7	PR → INT	−0.065**	0.03	2.29	[−0.12, −0.02]	S	0.014
H8	PT → INT	0.143**	0.05	2.75	[0.05, 0.22]	S	0.027
H9	SN → INT	0.131**	0.05	2.80	[0.06, 0.21]	S	0.034
Mediation analysis							
H10	PEOU → ATT → INT	0.016	0.04	0.37	[−0.05, 0.09]	NS	
H11	PU → ATT → INT	0.369**	0.06	6.55	[0.28, 0.47]	S	
Moderation analysis							
H12	PEOU*KT → INT	−0.019	0.02	0.78	[−0.06, 0.02]	NS	
H13	PU*KT → INT	0.032	0.02	1.58	[0.00, 0.07]	NS	
H14	AW*KT → INT	−0.017	0.03	0.66	[−0.06, 0.02]	NS	
H15	PR*KT → INT	0.007	0.02	0.33	[−0.03, 0.04]	NS	
H16	PT*KT → INT	0.009	0.02	0.45	[−0.03, 0.04]	NS	
H17	SN*KT → INT	0.020	0.02	0.91	[−0.02, 0.05]	NS	

Note(s): $*p < 0.05$. $**p < 0.01$., SE = Standard Error, S = Supported; NS = Not Supported; CI = Confidence Interval

($\beta = -0.065$). Other two relationships, such as PEOU → INT ($\beta = 0.025$) and AW → INT ($\beta = 0.055$) had very small path co-efficient and were insignificant. Therefore, H3, H5, H7, H8, and H9 are supported but not H4 and H6.

Next, this study investigated the significance of mediating effect following the bootstrapping techniques in Preacher and Hayes (2008). The findings in Table 7 show that ATT was a strong significant mediator between PU and INT ($\beta = 0.369$) with variance accounted for (VAF) of 73.51%. Also, a zero "0" did not straddle between the lower and upper limit of 95% CI [0.28, 0.47], demonstrating a significant mediating effect. However, another mediating path relationship (PEOU → ATT → INT) was not statistically significant. Therefore, H11 is supported, but H10 is unsupported.

This study also investigated the moderating effect of KT on each path relationship of the research model. Results in Table 6 exhibit that none of the interaction effects was significant at 95% CI. This finding indicated that the level of KT amongst the bank client did not strengthen the relationships between antecedents (i.e. PEOU, PU, AW, PR, PT and SN) and the outcome variable (INT). Hence, H12, H13, H14, H15, H16 and H17 are not supported.

As one of the major statistical objectives of SEM is to estimate the prediction accuracy of the research model, coefficient of determination (R^2), effect size (f^2) and Stone-Geisser's Q^2 value were evaluated (Hair *et al.*, 2017b; Sarstedt *et al.*, 2017). Results showed that the proposed research model explained 54.2% variance in ATT and 74.1% variance in INT. According to Chin (1998), an R^2 value of 0.67, 0.33, and 0.19 indicates a substantial, moderate and small level of prediction accuracy of a structural model. Hence, the research model has a moderate to a substantial level of prediction accuracy based on the R^2 value. It is also suggested that researchers should assess the practical significance of path relationships using effect size (f^2) categorised as large ($f^2 = 0.35$), medium ($f^2 = 0.15$) and small ($f^2 = 0.02$) (Cohen, 1988; Hair *et al.*, 2017b). Results in Table 6 demonstrate that in predicting ATT, PU has a large effect size of 0.399. Besides, in predicting INT, ATT has a strong effect size($f^2 = 0.359$), whereas other antecedents have a marginally small practical effect. Therefore, it can be deduced that client INT in banking is highly subjected to their ATT in banking and PU. Finally, setting an omission distance of 7, the results of Stone-Geisser's Q^2 exhibited that both ATT ($Q^2 = 0.484$) and INT ($Q^2 = 0.608$) have a large predictive relevance (Hair *et al.*, 2019). Table 7 outlines the findings of structural model analysis.

We also added control variables such as gender, age and education to investigate the robustness of estimated relationships. As there were few respondents with master's degree and PhDs (34 out of 302 respondents), we categorised education as "Diploma or below and Degree or above" while gender and age variables were considered according to the question asked. Results in Table A3 demonstrated that estimated relationships of the primary model (Model 1) did not have any significant deviations compared to estimations in the model with control variables (Model 2). Besides, amongst the control variables, education only was significant. Therefore it can be argued that estimated findings concerning the proposed model are robust.

5. Discussion and implications

This study offers practical implications for the management of banks. The empirical findings of this research confirmed that seven factors (i.e. AW , PR , PT, SN, ATT , PU , and PEOU) account for 74.1% of variance to the AI adoption intention in banking services. The findings explain that all these seven variables are essential for predicting AI adoption intention. However, all the hypothesised relationships between these predictors and the dependent variable were not statistically significant (refer to Table 7). Coherent with previous studies (i.e. Charbaji and Mikdashi, 2003; Rehman *et al.*, 2012), an insignificant relationship between AW and INT banking explains that a higher level of AW does not influence the client to adopt AI in banking services. Having a higher level of AW about AI, clients are aware of the benefits of using this technology in banking transactions. Still, they might be unsure whether the said benefits can be practically ensured. That is why the results were found insignificant between AW and AI intention (H6) but significant between PU and AI intention (H5). Despite this insignificant finding (H6), creating AW about AI technology and its benefits cannot be ignored. Bank managements are encouraged to initiate extensive marketing communication efforts to spread information concerning the benefit of innovation services using AI technology in the banking industry. Similarly, complementing the past literature (i.e. Faqih, 2016; Gefen *et al.*, 2003; Roca *et al.*, 2009), the relationship between PT and INT in banking was found significant and positive. Building trust in the use of new technology in banking transactions can increase the user's intention to adopt new technology. Concerning SN , a significant positive influence explains that individuals are more likely to adopt AI banking when they receive good recommendations in the banking service from their friends and families. In the purchasing of services, consumers heavily rely on opinions from the close networks of friends and family, social influencers. Gursoy *et al.* (2019) revealed that social influence plays a significant role in customers' intention to adopt or use AI devices. Hence, decision-makers in the banking industry should create opinion leaders from existing clients and/or renowned personalities to promote the benefits of AI in banking services using social media and traditional media platforms. Besides, creating opinion leaders could be one of the effective strategies in spreading positive word of mouth about AI in banking services.

PR was also found to have a significant negative but small effect on the INT in banking. This finding explicates that although a higher level of risk perceptions leads to lower adoption of AI in banking or vice versa, the practical significance of this relationship is low. The resulting lower effect of risk on AI intention could be due to AI banking being relatively new in the market; hence the risk perception of AI technology is still not entirely materialised into consumers' understanding. The qualitative study also revealed that the PR of data privacy and security is one of the major challenges in implementing AI technology in banking services. Generally, the banking service is often characterised as intangible, heterogeneous and uncertain (Alalwan *et al.*, 2016). Therefore, the decision-makers in the banking industry should take the necessary steps to seal the privacy and security issues in banking transactions. Although PU was found to have a significant positive effect, PEOU was insignificant in affecting INT in banking services. The findings suggest that bank clients prioritise the benefits of using AI over user-friendliness. However, in the literature, PU and ease of use are the important drivers of adopting new technology (Caffaro *et al.*, 2020). Such findings in the Malaysian context can be attributed due to the emergence of a new system unknown to the client. Clients may perceive that the usage complexity of AI is similar to other online technology such as online banking, operating smart devices. In this era, people are familiar with basic smart technologies like smart devices, online transactions, for which bank clients may feel confident in using new technology. Hence, PEOU may not be a significant predictor of AI adoption in banking services. Despite these findings, AI in banking services should be user friendly, easy to use while offering greater benefits to the clients.

This study also confirmed that ATT had the largest positive significant ($\beta = 0.518$) effect on the INT in banking services. It was quite expected that a favourable attitude toward an object leads to a higher level of consumer response (Albaity and Rahman, 2019). However, developing a positive attitude requires some efforts by the providers. The findings also support that PU and PEOU accounted for 54.2% of the variance in explaining ATT . Amongst these two predictors of attitude, PU had a large significant positive influence ($\beta = 0.711$) on creating a favourable attitude toward AI in banking services. Whereas the effect of PEOU on attitude was small and insignificant ($\beta = 0.031$). Due to these findings concerning attitude (both as the predictor and criterion variable in the theoretical model separately), it is useful to know whether attitude mediates the relationship between these two predictors and INT in banking services. Besides, knowing the direct effect of PU and PEOU on AI intention and an indirect effect through attitude would offer a comprehensive understanding of the role of these two predictors on AI adoption. Thus, this study investigated the mediating role of attitude between these two predictors and INT in banking services. The results demonstrated that attitude was a significant mediator between PU and AI adoption only. These findings related to attitude postulate that building a positive or favourable attitude toward the use of AI in banking services would be a winning strategy that can be materialised by ensuring the effectiveness and benefits of using AI. In the banking service, the adoption of AI should mitigate clients' safety and security concerns while offering greater convenience and user-friendliness of the new system. The findings from the qualitative study are also aligned with these empirical results. Bank professionals also assume that consumer experience, satisfaction and security concerns are amongst the top priorities for implementing AI in the banking service. However, lack of proper IT infrastructure, regulatory system and potential security threats are prevalent in this sector. Hence, policy makers in the banking sector should come forward to overcome these challenges concerning the implementation of AI.

This study also found that level of KT strengthens or weakens the relationships affecting the INT. Surprisingly, none of the moderating hypotheses was supported. A person having sound technological know-how intends to adapt to new technology quickly compared to those who are not technologically savvy (Nagdev *et al.*, 2021). The probable explanations concerning the insignificant moderating effect of KT would be, (1) the client participating in this research had little understanding and skills related to the technology. This scenario is quite usual in this digital era where consumers are tech-savvy; (2) As AI is a new phenomenon in the banking service in Malaysia, clients are not quite familiar with the specific knowledge required to use AI in banking services. They might assume that AI in banking services is similar to basic knowledge about technology such as Internet browsing skills, operating computers, using smartphones etc. As a consequence, KT did not have any significant moderating effect on the hypothesised relationships. In fact, client knowledge in AI technology is essential for increasing the use of bank services operated by AI technology. Therefore, bank management should provide audio and visual instructions concerning how to use bank services transformed with AI technology. Besides, both online and offline support services teams should remain on standby to solve any problems, difficulties faced by bank clients.

6. Conclusions, limitations and future research

AI in the banking sector has a great potential to create more efficient business processes and offer better-personalised services to customers. This study seeks to understand the challenges in implementing AI and the client's behavioural intention of adopting AI in the banking sector. Hence, this study employs a qualitative research approach to explore the challenges in implementing AI in banking services, along with quantitative research design to examine the relationships between predictors (AW, PT, PR, SN, ATT, PU, and PEOU) and INT in banking. Qualitative study reveals that lack of regulations, security and privacy risk, lack of IT infrastructure are the key challenges in implementing AI technology in banking services.

This study adopts the TAM by incorporating important variables such as AW, PR, PT, SN and KT. This study thus contributes to the emerging literature on AI by including AW, PR, trust, SN and KT with TAM. The quantitative investigation reveals the essential factors that can drive the client's INT. The study findings provide some useful insights for bank management in formulating AI banking strategies. For instance, while comparing the effects of PU and PEOU, it is important to understand that PU had a much greater influence on developing a favourable ATT. In contrast, the attitude had the strongest direct effect on the INT in banking. The mediating effect of attitude also substantiated that the effect of PU on intention via attitude was the strongest and significant. Therefore, increasing the usefulness of AI technology should give higher importance to banking services and applications. Furthermore, to increase consumer INT in banking, the study recommends that the bank design an effective marketing strategy to increase clients' trust, create opinion leaders, lower risks, and raise the AW level amongst customers regarding the benefits of AI. For those who have less knowledge of technology, the use of AI banking services would be risky. Bank managements should take necessary steps by increasing the protection and security measures, ensuring a better customer service experience to make the AI banking service more trustworthy and enjoyable.

Despite the above implications of this study, some limitations warrant further research:

(1) From a methodological perspective, this study relies on self-reported data collection through a survey. Such data may not be very precise. In the future, to increase accuracy, researchers are suggested to increase the sample size and adopt other methods of data collection such as field experiments.

(2) Although KT has been conceptualised as a moderator in this study, the results were not significant. Respondents might rate the questions regarding knowledge in basic technology such as Internet use, basic computer skills, etc., rather than knowledge specific to AI. Thus, future researchers could specify the questions about knowledge in AI technology and investigate the moderating effects.

(3) As AI banking is relatively a new phenomenon in the Malaysian banking sector, people need more time to adapt to this technology.

The results of this study could change over time once AI technology has been integrated widely into the business environment. Therefore, further research is necessary to find differences in consumer behaviour between early adopters and the late majority.

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Appendix 1

No	Questions
1	How important is AI for the banking system in Malaysia?
2	Any specific use of AI in the banking sector of Malaysia?
3	What are some of the challenges that bank in Malaysia faces in terms of AI adoption?
4	Do you think customer awareness level influences customers' intention to adopt AI in banking services?
5	Do you think risk perception is related to customers' intention to adopt AI in banking services?
6	Do you think usefulness influences customers' intention to adopt AI in banking services?
7	Do you think ease of use influences customers' intention to adopt AI in banking services?
8	Do you think trust influences customers' intention to adopt AI in banking services?
9	Do you think social norms influences customers' intention to adopt AI in banking services?
10	Do you think knowledge in technology helps customers to use AI banking services?

Table A1. Questions used for interview

Appendix 2

Construct	Code	Item	Source
Awareness	AWS1	I receive enough information about AI enable technology in banking services	Al-Somali *et al.* (2009), Rehman *et al.* (2012)
	AWS2	I receive enough information about the benefits of AI enable technology in banking services	
	AWS3	I receive enough information of using AI enable technology in banking services	
	AWS4	I never receive enough information of using of AI enable technology in banking services	
Perceived ease of use	PEOU1	Learning to use AI enable technology in banking is easy to me *(e.g. Chatbots: chat based virtual assistant)*	Belanche *et al.* (2019)
	PEOU2	I would find it easy to manage banking investments using AI banking enable technology in banking *(e.g. Chatbots: chat based virtual assistant)*	
	PEOU3	I would find it easy for me become skilful at using AI enable technology in banking *(e.g. chatbots: chat based virtual assistant)*	
	PEOU4	I would find it easy to interact with AI in banking as it does not require a lot of my mental effort *(e.g. chatbots: chat based virtual assistant)*	

(*continued*)

Table A2. Measurement items and sources

Construct	Code	Item	Source
Perceived usefulness	PU1	It would improve my performance in managing banking investments by using AI enable technology in banking *(e.g. chatbots: chat based virtual assistant)*	Belanche *et al.* (2019)
	PU2	It would improve my productivity in managing banking investments by using AI enable technology in banking *(e.g. chatbots: chat based virtual assistant)*	
	PU3	It would enhance my effectiveness in managing banking investments by using AI enable technology in banking *(e.g. chatbots: chat based virtual assistant)*	
	PU4	I would find AI enable technology in banking useful in managing banking investments *(e.g. chatbots: chat based virtual assistant)*	
Perceived risk	PR1	Using AI enable technology in banking services subjects my banking account to potential fraud	Alalwan *et al.* (2016), Featherman and Pavlou (2003)
	PR2	Using AI enable technology in banking services subjects my banking account to financial risk	
	PR3	I think using AI enable technology in banking puts my privacy at risk	
	PR4	AI enable technology in banking might not perform well and will create problems with my bank account	
Perceived trust	PT1	The AI banking enable technology services are trustworthy	Payne *et al.* (2018), Susanto *et al.* (2016)
	PT2	The AI banking enable technology provides banking services in my best interest	
	PT3	The AI banking enable technology offers access to sincere and genuine banking services	
	PT4	This AI banking enable technology performs its role of providing banking services well	
Subjective norms	SN1	Generally speaking, I would take the advice from people who are important to me to use AI banking enable technology	Belanche *et al.* (2019)
	SN2	Generally speaking, I would like to go along with my group of friends to use AI banking enable technology	
	SN3	People important to me think I should use AI banking enable technology	
	SN4	People I know could influence me to try out AI banking enable technology for managing banking investments	
Attitude toward AI	ATT1	Using AI banking enable technology for managing banking investments seems like a good idea	Belanche *et al.* (2019)
	ATT2	I Like the idea of using AI banking enable technology for managing personal banking investments	
	ATT3	Using AI banking enable technology for implementing my banking investments seems like a wise idea	

Table A2.

(*continued*)

Construct	Code	Item	Source
Intention to adopt AI in banking	INT1	I Intend to use AI banking enable technology for managing banking investments	Belanche *et al.* (2019)
	INT2	Using AI banking enable technology for managing banking investments is something I would do	
	INT3	My intention is to use AI banking enable technology service rather than any human financial advisor	
Knowledge in technology	KT1	I know pretty much about technology. *e.g. computer, laptop, tablet, mobile phone etc)*	Lin and Filieri (2015)
	KT2	I am an expert user of technology. *(e.g. computer, laptop, tablet, mobile phone etc)*	
	KT3	I know pretty much about how to use technology. *(e.g. computer, laptop, tablet, mobile phone etc)*	

Note(s): KT = Knowledge Technology, AW = Awareness, PEOU = Perceived ease of use, PU = Perceived Usefulness, PR = Perceived Risk, PT = Perceived Trust, SN = Subjective Norms, ATT = Attitude toward AI, INT = Intention to adopt AI in banking

Table A2.

Appendix 3

Hypotheses		Model 1 Std. Beta	SE	*t*-value	*R*-square	Model 2 Std. Beta	SE	*t*-value	*R*-square
H1	PEOU → ATT	0.031	0.081	0.379	0.542	0.031	0.081	0.379	0.542
H2	PU → ATT	0.711**	0.077	9.291		0.711**	0.077	9.295	
H3	ATT → INT	0.518**	0.059	8.826	0.741	0.504**	0.060	8.474	0.751
H4	PEOU → INT	0.025	0.056	0.439		0.007	0.060	0.121	
H5	PU → INT	0.133*	0.069	1.918		0.134*	0.071	1.885	
H6	AW → INT	0.055	0.037	1.498		0.070*	0.039	1.787	
H7	PR → INT	−0.065*	0.029	2.292		−0.049*	0.029	1.708	
H8	PT → INT	0.143**	0.052	2.749		0.149**	0.052	2.835	
H9	SN → INT	0.131**	0.047	2.795		0.119**	0.045	2.632	
Control variables									
	Gender → INT					−0.048	0.032	1.532	
	AgeG1 → INT					0.041	0.040	1.014	
	AgeG2 → INT					−0.020	0.038	0.538	
	EduG → INT					0.062*	0.031	2.012	

Note(s): *$p < 0.05$. **$p < 0.01$., SE = Standard Error

Table A3. Model estimation with control variables

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