Heliyon 9 (2023) e21130

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Users' fintech services acceptance: A cross-sectional study on Malaysian Insurance & takaful industry

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ARTICLE INFO

Keywords:
Fintech services acceptance
Delone and Mclean IS success model
Perceived risk
UTAUT2
Malaysia's insurance and takaful industry

ABSTRACT

The emergence of fintech services in the insurance industry has been a transformative force, reshaping how insurance companies operate, how policies are sold, and how customers interact with their insurers. Financial technology developments, also known as "fintech," are changing how financial services are offered, presenting novel possibilities for the insurance industry worldwide. However, in the Malaysian insurance and takaful industry a good number of customers are still dependent on conventional channels like agents and brokers continue to be important sources for purchases and payments related to insurance instead of using Fintech services. The insurance industry's success and growth are highly dependent on adopting technological services offered by companies to make the process efficient and profitable. So, this study aimed to empirically identify the determinants influencing Malaysia's insurance and takaful industry customers to accept the fintech services for insurance-related transactions and activities. The research combined two prominent technology adoption models UTAUT2, and Delone and Mclean IS Success, and proposed a new research framework. The data for the research has been collected from the insurance and takaful industry customers through Google Forms. Finally, 350 responses were received. The PLS-SEM method was utilized to investigate the data by Smart PLS 3.2.9 software. The result of the study revealed that effort expectancy, information quality, service quality, system quality, and perceived risk impact behavioral intention to use fintech services (BI). In addition, the actual use of fintech services is impacted by behavioral intention. Nevertheless, no impact was found in the case of performance expectancy and social influence on BI. The findings of the study are helpful for academicians, researchers, and insurance companies to explore determinants for fintech services acceptance.

1. Introduction

Financial technology (Fintech) is one of the most emerging phenomena today. This technology is used in almost every sector to manage enterprise operations, especially in the financial industry. It mainly focused on improving the service quality of financial services using Information Technology (IT) [1]. Fintech is a term that is frequently used to describe the ongoing trend of new digital

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https://doi.org/10.1016/j.heliyon.2023.e21130
Received 24 March 2023; Received in revised form 14 October 2023; Accepted 16 October 2023
Available online 18 October 2023

financial services, according to Pazarbasioglu et al. [2]. Digital payments, digital insurance, and digital financial services are currently the most frequently used fintech services in the insurance sector. Like any other financial institution, insurance companies are adapting to technological changes and adapting fintech services in their business. It involves the utilization of digital platforms, data analytics, artificial intelligence, and other technological progress to improve diverse facets of the insurance industry, such as policy underwriting, claims processing, customer experience, and risk evaluation [3]. One of the most promising fintech systems for the insurance business is the digital payment platform. When financial organizations exchange electronic signals instead of checks, cash, or other negotiable items, this is regarded as a type of financial transaction [4]. Mobile payments are the most typical type of digital payment. Additionally, digital insurance is the use of technology and digital channels by insurance providers to run their operations and provide policy services [5]. Customers can acquire insurance through this service, which is automated for quicker claims processing and innovative tailored products, among other things. Moreover, financial services that use digital technologies to assist consumers are called digital financial services [2]. Robo-advisors, application programming interfaces (API), and other similar services are the most prevalent digital financial services. These programs offer users online advice services for making financial decisions [6]. Since 2015, usage of fintech services has increased. According to the EY Fintech Adoption Index (2019) [7], about 64% of individuals globally have adopted fintech services. The index also showed that about 96 % of consumers worldwide are at least familiar with one fintech service. In addition, one out of every two consumers and three out of every four people use an insurance fintech service. In addition, 14 % of consumers are aware of fintech insurance-related services.

There are now 55 active companies in Malaysia's insurance and Takaful industries [8]. In Malaysia, digital platforms are widely used, with 64 % of respondents using them at least once every week. With 89% of respondents utilizing them at least once every three months, e-commerce applications or websites like Shopee in Malaysia are the most well-liked. Next in popularity are digital payment apps like Touch n' Go (75%) [9]. Online informational and commercial insurance purchases are also on the rise. However, in Malaysia, customers still depend on conventional channels like agents and brokers, which are important sources for insurance purchases and payments [10]. The acceptance of fintech services in the insurance and takaful industry for online insurance purchases is lower compared to other ASEAN countries [11]. One of the core reasons customers might not be fully aware of the range of fintech services available. In addition, the increasing volume of cybersecurity incidents and concerns about information security and privacy risks have raised doubts regarding the sufficiency of current security protocols and standards [12]. If they perceive that their information could be at risk, they are more likely to avoid using fintech platforms. In Malaysia, the insurance and takaful industries are a vast red ocean. It is still evolving and mutating as it adapts and forges new paths in digitization and technological development to influence the sector's future. Determining the factors influencing consumers' acceptance of fintech services in the Malaysian Insurance and takaful industry is essential.

Considering the expanding fintech services acceptance in different industries, several scholarly emphases have been placed on understanding consumers' intention towards adopting fintech services. Nevertheless, gaps in the existing body of knowledge require attention. Investigating how fintech relates to customer adoption of its services is still growing, requiring more comprehensive exploration. While prior studies have provided valuable insights into the drivers of customer fintech adoption [13–15], the focus has predominantly centered on customer intentions for fintech adoption from a technological standpoint. In this regard, the influence of user perspectives, and quality dimension needs to be incorporated to determine the influence acceptance of fintech services. Given the heightened public awareness regarding security and personal data, the aspect of perceived risk becomes a pivotal factor impacting fintech usage [16,17] thereby underscoring the importance of evaluating the role of perceived risk in determining the insurance customers' acceptance of fintech services. Secondly, the existing body of research investigating the Unified Theory of Acceptance and Use of Technology (UTAUT2) and the Delone and Mclean Information Systems Success Model (ISSM) have investigated consumer behavior in response to technology-driven changes. Among the transformative evolution of digital technologies, fintech is a fundamental technology underpinning e-commerce, mobile banking, online-to-offline (O2O) services, and fintech adoption. Scant research integrated the two prominent theories, UTAUT2 and Delone and Mclean Information Systems Success Model [18].

In the process of conducting our comprehensive literature review, we identified a scarcity of studies centered around Fintech acceptance, specifically concerning the adoption of Fintech services acceptance in the Insurance industry. Considering this gap, our research distinguishes itself from existing studies. Firstly, our investigation examines the factors influencing the adoption of Fintech services acceptance, specifically focusing on the three dimensions from the UTAUT2 model (performance expectancy, effort expectancy, social influence) and three dimensions from the Delone and Mclean Information success model (system quality, service quality, information quality). Unlike previous research, which often failed to incorporate user perspectives and quality dimensions, we consider these dimensions. Furthermore, the crucial role of user-perceived risk in the realm of Fintech services acceptance has been understudied in prior literature. This study also integrated the concept of perceived risk to analyze insurance customers' intentions to accept Fintech services. Secondly, earlier studies predominantly explored fintech adoption in the banking industry. We meticulously scrutinize the user's behavioral intention and actual use of fintech services in the context insurance and takaful industry, offering a novel vantage point. Thirdly, our research goes beyond theoretical contributions and successfully puts into practice a conceptual framework, yielding valuable policy implications, particularly relevant to Malaysian Insurance and Takaful industry stakeholders. By doing so, we aim to bridge the existing gap in the scholarly discourse by shedding light on the factors that shape users to accept Fintech services. Consequently, our formulated research questions are tailored to gain insights into the behavioral intentions and users' acceptance of fintech services, thus advancing our understanding in this domain.

RQ1. Do performance expectancy, effort expectancy, and social influence affect the insurance company customers' behavioral intention to accept fintech services?

RQ2. Do information quality, system quality, and service quality affect the insurance company customers behavioral intention to

accept fintech services?

RQ3. Does perceived risk affect the insurance company customers' behavioral intention to accept fintech services?

RQ4. Does insurance company customers behavioral intention affect the actual use of fintech services?

The remainder of the paper will be divided into four sections. Part 2 will go over the literature, the proposed study framework, and the formation of hypotheses. The research methodology, sampling, data collection, and analysis procedure will be covered in Section 3. Part 4 will create and discuss the study findings. Finally, section 5 will discuss the conclusion, contribution, limitations, and future research directions.

2. Literature review & hypothesis development

2.1. Fintech services acceptance

FinTech contributes to understanding the fast evolution of the financial system and financial institutions. Financial technology advancements have enabled users to use fintech applications for payment processing, savings, borrowing, risk management, and obtaining financial advice [19]. Because of digital advancements in other industries, consumer demand for technology-based financial solutions has increased [20]. To meet customers' demands, technological companies are introducing more accessible and cost-effective methods of money transfer, borrowing, and investing [21]. FinTech has been adopted in most industries, especially after Covid-19 [22]. However, despite the advancement in technological development, the services of fintech are implemented selectively [23]. Several studies have been conducted on fintech adoption in the Malaysian context earlier [24–26]. Sharma and Sood [27] explored the adoption of the Internet of Things (IoT) in fintech apps and services in the Indian insurance industry. This study only focused on the available AI services in the Indian insurance market. In addition, Bian et al. [28] explored how fintech is reshaping the Insurtech and insurance market in China. Most of the earlier studies focused on fintech adoption in the insurance industry from the company perspective. Nevertheless, rare studies are conducted on fintech services acceptance from the users (customers) context. So, this study will identify the factors that influence Malaysian insurance and takaful industry customers' acceptance of Fintech services like digital payment, digital insurance, and digital financial services.

2.2. UTAUT2 model

The Unified Theory of Acceptance and Use of Technology (UTAUT) was initially formulated in 2003 by Venkatesh, Morris, and Davis. The UTAUT theory was established by Venkatesh et al. [29], who conducted a comprehensive review and comparison of eight different models in their research. This theory was initially developed for new technology adoption among the employees of the organization. UTAUT2 is an expansion of the UTAUT model established in 2012 by Venkatesh, Thong, and Xu. Later, Venkatesh et al. [30] modified the model in response to changes in the consumer usage environment and introduced new components to the UTAUT. The model now includes three new constructions. These components include hedonic motivation, price value, habit, and others, in addition to performance expectancy, social influence, effort expectancy, and facilitating conditions from Venkatesh et al. [29] UTAUT model. This UTAUT2 model outperformed the original UTAUT model in terms of the variance to describe behavioral intention, increasing it to 56%–70 % and technology use to 40%–52 %. The model is frequently used to explain the behavioral factors influencing the intention to utilize new technologies [31]. It has been used in applications ranging from non-technological service acceptance [32] to cloud computing technology acceptance [33]. The advantages of the UTAUT2 model have led to its widespread use. By including cognitive antecedents into UTUAT, Khazaei [34], for instance, utilized it to explain why Malaysian SMEs adopted blockchain technology. Personal creativity, perceived security, and perceived trust were all examined. To determine the criteria for implementing a fintech P2P lending platform in Indonesia's small food industry, Najib et al. [14] included the UTAUT2 model. Al Nawayseh [35] integrated an enhanced valence framework into the extended version of UTAUT to identify fintech adoption in Jordan amid the Covid-19 outbreak. In addition, Khatun and Tamanna [36] used the UTAUT model to study the adoption of fintech in financial institutions in Bangladesh and included factors including perceived reliability, self-efficacy, nervousness, and added value. The increased user acceptability of fintech applications was also examined by Yohanes et al. [37], who found that effort expectancies, social influence, and facilitating conditions are essential determinants of fintech adoption. Choi [38] countered that UTAUT2 failed to show the components that contribute to enjoyment while including hedonic motivation as a predictor of behavioral intention. In addition, "Habit" is not a concept that can be used to analyze newly released technologies [39]. Cost or price is not always a reliable predictor of technology uptake [40]. Based on the literature and arguments from the authors, UTAUT2 has been used as an underpinning theory for technology adoption studies where performance expectancy, effort expectancy, and social influence showed a significant impact on behavioral intention to use in Asian cultural context. As this study is based on Malaysian insurance and takaful industry, this study will utilize performance expectancy, effort expectancy, and social influence as the indicators of fintech services acceptance.

2.3. Delone and McLean information system success model

Delone and McLean developed the Delone and McLean information system success model in 1992 [41]. The model included information quality and system quality to measure the intention to use, user satisfaction, and organizational impact. Later author revised the D & M model in 2003 [42]. Service quality was included in the new version of the model to measure intention to use the information systems. Several technology adoption and information system studies have used and validated the D&M model. It has been

used in evaluating the success of e-commerce systems [43], acceptance of e-learning platforms [44], mobile banking individual performance [45], and many other technology acceptance [46,47]. The revised D&M model and the UTAUT2 model serve as the basis for this study.

This study will utilize three dimensions, information quality, service quality, and system quality, to measure customers' intention to use. Because the concept of information system quality is linked to system output that benefits users. In addition, system quality is also an important dimension to assessing the system's overall efficiency; good system quality will motivate customers to use FinTech application applications. Moreover, service quality ensures the available support that customers will receive from the company for using a fintech platform or application.

Another critical dimension is perceived risk. The perceived risk significantly impacts how users behave when using technology services. Perceived risk in consumer innovation research has received much attention in the literature. Due to security and financial concerns, perceived risk is one of the most critical variables that may have a negative impact on the adoption of fintech [48]. To use fintech services, users have to share their personal information and financial information with third-party vendors so that they might perceive several concerns, including internet problems, problems with their security, unlawful transactions, and documentation [49]. So, this study will incorporate perceived risk as one of the dimensions of fintech services acceptance by Malaysian Insurance and takaful Industry customers.

2.4. Hypotheses development

2.4.1. Performance expectancy (PE)

Performance expectancy can be defined as the degree to which an individual's performance of performing any task improves due to using a technology or syste [30]. In this study context, it refers to the improved performance of using fintech platforms for insurance-related activities. Performance expectancy is one of the crucial indicators for technology adoption. Rahim et al. [25] investigated Islamic Fintech adoption among Malaysian millennials and discovered that performance expectancy substantially influenced behavioral intention. Furthermore, Alwi et al. [50] investigated fintech adoption in Malaysia's fourth industrial revolution era and discovered that performance expectancy influenced fintech adoption favorably. Based on the prior findings on the Malaysian context, the following hypothesis is proposed in this study.

H1. Performance Expectancy positively impacts Behavioral Intention.

2.4.2. Effort expectancy (EE)

Effort expectancy measures how convenient a system is thought to be to use by an individual [51]. Effort expectancy is considered a positive indicator of technology adoption in prior studies. In the instance of e-wallet adoption in Malaysia, effort expectancy had a considerable positive effect on the intention [52] Furthermore, Urus et al. [53] conducted a comparative study on fintech payment system acceptance among Indonesian and Malaysian fresh graduates and discovered that effort expectancy positively influenced fintech payment system adoption. Based on the discussion on earlier technology adoption studies in Malaysian and near regions, this study proposes the following hypothesis.

H2. Effort Expectancy positively impacts Behavioral Intention.

2.4.3. Social influence (SI)

Social influence refers to the extent to which a person believes others' opinions are essential when using a new system [51]. Many studies used social influence as a positive indicator of technology adoption. In a study focused on developing countries' open-source software adoption, social influence showed a positive impact [54]. Similarly, social influence positively impacted fintech adoption in the small food business [14]. A similar conclusion was reached in a study on the adoption of the internet of things (IoT) [55]. From a developing country perspective social influence showed a significant impact on behavioral intention. As the context of the study is based on a developing country like Malaysia, this study in light of the discussion puts forth the following hypothesis.

H3. Social Influence positively impacts Behavioral Intention.

2.4.4. Information quality (IQ)

Information quality is the level of performance that a system offers to an individual user [42]. It is also defined as an information system's output standard [56]. Information quality is a crucial element an information system offers final users. Information quality is also important for fintech users to perform transactions on the fintech platform for insurance-related activities. In a study conducted in Taiwan, Huang et al. [57] found a significant positive impact of information quality on behavioral intention to use the mobile library system. In addition, Komiak [58] found that the user's perceived information quality significantly impacted behavioral intention. From a developing country perspective, information quality showed a significant impact on behavioral intention. As the context of the study is based on a developing country like Malaysia, this study proposes the following hypothesis for information quality.

H4. Information Quality positively impacts Behavioral Intention.

2.4.5. System quality (SQ)

System quality evaluates a system's dependability, usefulness, responsiveness, and availability [42]. Good user ratings of the system may influence the user's attitudes and behaviour. Good system quality is correlated with high system reliability, which may

increase the likelihood of using a system like a fintech [59]. Ramayah et al. [60] studied e-learning system continuous adoption in Malaysia and found that system quality is positively related to intention to use. In addition, system quality positively influenced the intention to use mobile learning [61]. Based on the prior study results on Malaysian context, this study proposes the following hypothesis for information quality.

H5. System Quality positively impacts Behavioral Intention.

2.4.6. Service quality (SEQ)

Service quality is the customer experience of services that can be compared to expectations to determine customers' perceived quality of services [62]. Service quality (SEQ) is considered crucial in differentiating services. When Abu-Taieh et al. [63] looked at Jordanians' continuing intention to utilize mobile banking, they discovered that service quality positively affects behavioral intent. Service quality was also identified as a promising predictor of the adoption of online transportation systems [64]. The following service quality hypothesis is proposed for Malaysian insurance and takaful industry fintech users based on the findings of earlier research on developing nations.

H6. Service Quality positively impacts Behavioral Intention.

2.4.7. Perceived risk (PR)

The perceived risk is the possibility of losses (or adverse effects) consumers may perceive when using technology to achieve their goals [65]. It is crucial to examine the perceived risk to comprehend consumer behavior since people tend to minimize benefits by avoiding or reducing risks rather than maximizing rewards by incurring them. When customers' worries are connected to novel technologies, their perception of danger will likely be reinforced [66]. According to Al-Saedi and Al-study Emran [67], in adopting mobile wallets, the risk is inversely connected to the intention to adopt. Moreover, perceived risk negatively impacted the intention to use online banking in Vietnam [68]. Risk is considered one of the crucial elements in the case of using technology services among Malaysians. Based on the prior study results and nature of Malaysian concern over risk, this study proposes the following hypothesis for information quality.

H7. Perceived Risk negatively impacts Behavioral Intention.

2.4.8. Behavioral intention (BI)

Behavioral intention is the extent to which a person has intentionally formed plans to engage in or refrain from taking future acts [69]. Several researchers argued that BI immediately impacts actual behavior and that a good assessment of intention may be used to

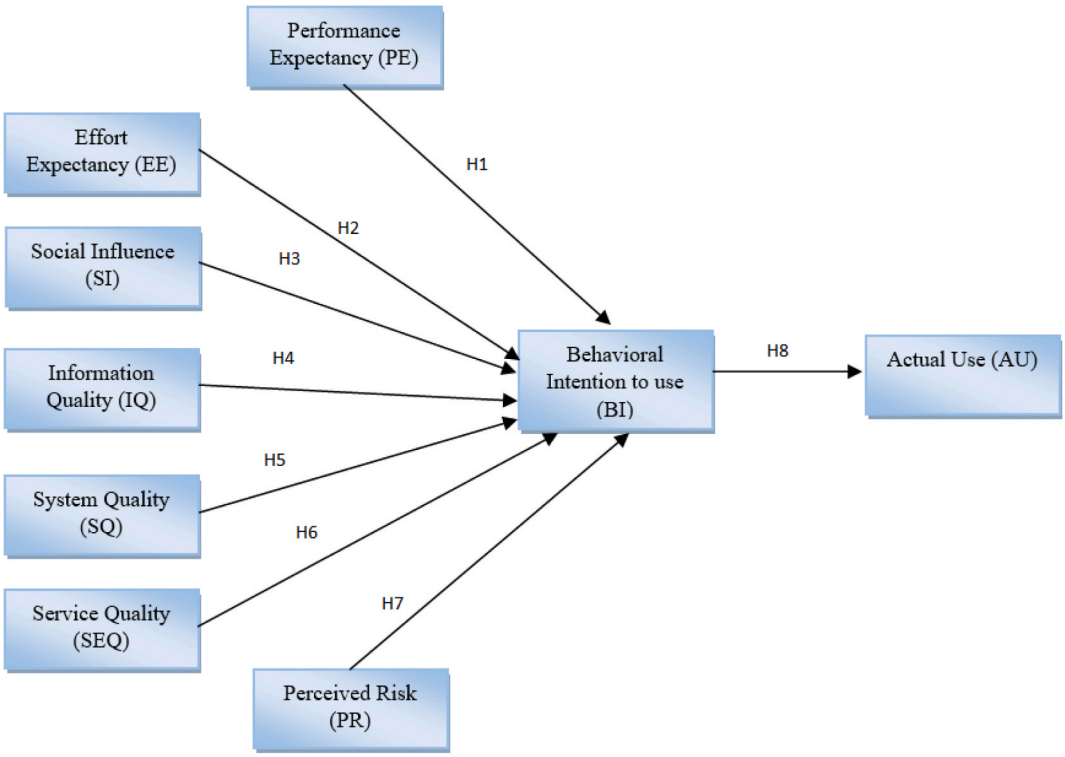

Fig. 1. Research framework.

predict it most accurately [70]. Most research studies on adopting technology discovered that behavioral intention has a favorable effect on actual usage behavior. For example, Khatun and Tamanna [35] investigated the fintech adoption among Bangladesh users of financial institutions and revealed that behavioral intention positively impacts actual usage behavior. A similar result was found in mobile money adoption In Ghana [71]. The results from the developing perspective showed the association between BI and Actual use. So, the following hypothesis is proposed for the Malaysian insurance and takaful industry customers context.

H8. Behavioral Intention positively impacts Actual Use.

The literature review indicates that rare research has been conducted on fintech services acceptance in Malaysia's insurance and Takaful industry. To address the theoretical gap, this study proposes the following research framework in Fig. 1.

3. Methodology

3.1. Research methods & measures

The study aims to identify the factors driving the customers of the insurance industry of Malaysia to accept fintech services. Therefore, the nature of the study is explanatory. It is evident from the prior literature on technology adoption that authors used explanatory research to identify the impact of variables on technology adoption [72]. The study applies positivist ontology, empirical epistemology, and quantitative methodology. The research is conducted for a single time. That means the study is a cross-sectional study. This study applies a deductive approach because the research is quantitative and requires identifying relationships between different variables. The study has utilized three variables from the UTAUT2 model (PE, EE, SI), three variables from the D & M Information Success Model (SQ, SEQ, IQ), and perceived risk from the literature. The measurement items for PE and EE are adapted from Rahim et al. [25], SI is adapted from Al-Nawayseh [35], and Chan et al. [73], IQ, SQ, SEQ are adapted from Tam and Oliveir [74], PR is adapted from Kim et al. [75], BI is adapted from Hu et al. [76], and AU is adapted from Gupta and Arora [77]. The measurement items are available in the Appendix section of the study.

The study utilizes partial least square structural equation modeling (PLS-SEM) to analyze the results. Fintech services in this research refer to digital payment, digital insurance, and digital financial services. In this research, unless specified otherwise, the study determined all constructs using seven-point Likert scales with multiple items. Participants are asked to express their level of agreement or disagreement with each statement on a scale ranging from 1, indicating "strongly disagree," to 7, indicating "strongly agree." The items used to measure both the independent and dependent variables in this study were sourced from established scales in the literature, with minor adjustments made to tailor them to the specific objectives of our research, ensuring their reliability and validity [78]. Structural equation modeling analysis comprises of measurement model assessment and structural model assessment. The study uses SMARTPLS 3.2.9 software to run the data collected through a Google survey questionnaire.

3.2. Data sampling & data collection method

To test the research hypotheses, the study uses an empirical examination utilizing a dataset comprising Malaysian consumers, one of the emerging countries in fintech adoption. Malaysia has a growing and diverse fintech ecosystem, with a range of startups, established financial institutions and technology companies actively participating. The country has made significant efforts to promote financial inclusion through fintech. Malaysia has attracted substantial fintech investment. In 2020, the country received over $1 billion in fintech funding, reflecting investor confidence in the market. Malaysia has high mobile and internet penetration rates, creating a conducive environment for fintech adoption, particularly in mobile payments and digital banking. Moreover, Digital payment methods, particularly e-wallets, have gained immense popularity in Malaysia. As of 2020, e-wallet transactions exceeded 1.3 billion,

Table 1
Study's demographic profile.

	Frequency	Percentage
Gender		
Male	216	61.7
Female	134	38.3
Age		
20+ – 30	93	25.6
30+ – 40	119	34.0
40+ – 50	97	27.7
50+ and above	41	12.7
Academic Qualification		
SPM/O Level	42	12.0
STPM/A Level	64	18.3
Graduate	147	42.0
Postgraduate	97	27.7
Do you use a fintech platform for insurance-related activities?		
Yes	311	88.9
No	39	11.1

reflecting a significant shift toward cashless payments.

Data is collected through an online survey questionnaire using Google Forms from Malaysian Insurance and takaful industry customers in three selected states from the Malaysian northern region Penang, Kedah, and Perlis. The online survey link is shared in these three states' selected insurance companies' customer care centers. Insurance customers who visited the customer care centers were allowed to participate in the survey. The interested respondents willingly participated in the survey. Informed consent has been received from the customers online in Google form for the survey.

The study uses a purposive (judgmental) sampling method because a judgmental sample chooses participants best positioned to offer the desired information [79]. According to Barclay et al. [80], the minimal sample size should be "ten times the largest number of formative indicators used to measure one construct" or "ten times the maximum number of inner model paths directed at a single construct in the inner model," whichever is larger. As per the rule the minimum sample size should be more than 80. Finally, 350 survey responses are collected online for data analysis, meeting the minimum sample size criteria. As it is not clinical research, institutional review board/ethical committee approval for this kind of study is uncommon or not required in Malaysia.

4. Findings and analysis

Data from Malaysian insurance and takaful industry clients has been gathered to aid the investigation. Table 1 below provides the study's demographic profile.

According to Table 1, the study respondents combined 63.1 % of males and 36.9 % of females. The age group of the respondents is highest, between 30+- 40 at 34 %, followed by 40+ - 50 (27.7 %), 20+ - 30 (25.6 %), and 50+ and above (12.7 %). The academic qualification showed that 69.7 % of the respondents are at least a graduate, and the rest, 30.3 % do not have a graduate degree. Approximately 88.9 % of the respondents said they use at least one fintech platform for insurance-related activities. However, 11.1 % don't use a fintech platform or a manual process to perform insurance-related activities.

4.1. Measurement model assessment

The measurement model assesses the reliability and validity of the measurement constructs. The research model consists of a total

Table 2
Outer loadings.

	AU	BI	EE	IQ	PE	PR	SEQ	SI	SQ
AU1	0.651								
AU2	0.789								
AU3	0.788								
AU4	0.727								
BI1		0.866							
BI2		0.862							
BI3		0.832							
EE1			0.856						
EE2			0.843						
EE3			0.855						
EE4			0.852						
EE5			0.848						
IQ1				0.824					
IQ2				0.856					
IQ3				0.613					
IQ4				0.809					
PE1					0.842				
PE2					0.876				
PE3					0.850				
PE4					0.868				
PR1						0.890			
PR2						0.898			
PR3						0.830			
PR4						0.872			
SEQ1							0.857		
SEQ2							0.859		
SEQ3							0.883		
SEQ4							0.827		
SI1								0.814	
SI2								0.845	
SI3								0.714	
SI4								0.775	
SI5								0.756	
SQ1									0.777
SQ2									0.833
SQ3									0.817

of nine independent and dependent variables. The below section will discuss the reliability and validity of the measurement constructs.

4.1.1. Common method bias

The investigation employed three distinct approaches to validate the potential presence of common method bias that could arise during PLS-SEM verification. Following the method proposed by Podsakoff et al. [81], an evaluation was undertaken to ascertain how a singular factor explains the variance across all observed variables in path analysis using principal component analysis. Earlier technology adoption studies followed the same criteria for common method bias [82,83]. In line with Harman's single-factor technique, a principal component analysis was performed on 36 observation variables, confirming the explanation at 43.136 %, a value below the 50 % threshold. Secondly, following the PLS-SEM verification procedure outlined by Kock [84], multicollinearity was assessed amidst latent variables. The outcome indicated that the variance inflation factor (VIF) remained within acceptable limits, ranging from the minimum value of 1.00 to the maximum of 3.13 without exceeding the threshold of 3.3. Thirdly, the approach by Lindell and Whitney [85] on market variables was utilized. A distinct marker variable (M1) was established, which exhibited minimal correlation with the existing latent variables. M1, representing the perceived trust of participants, displayed correlations ranging from 0.026 to 0.197 without statistical significance. These three verification methodologies collectively mitigated the potential for common method bias issues within our latent variables.

4.1.2. Reliability & convergent validity

To examine measurement model assessment, start by looking at the indicator loadings. Use of loadings greater than 0.708 is advised [86]. Cronbach's alpha and composite reliability measures are then utilized to verify the internal consistency reliability analysis. The reliability scores for each structure should be more than 0.70, indicating a high degree of internal consistency [86]. The construct's ability to explain component variation is measured for convergent validity [86]. Convergent validity is evaluated using the average variance extracted (AVE), and a minimum value of 0.50 is needed. Table 2 illustrates the outer loadings of the measurement items, and Table 3 shows Cronbach's alpha, composite reliability, and AVE values. Tables 2 and 3 revealed that all the values met the minimum threshold; however, the AU1 and IQ3 constructs were retained in this investigation because removing them had no positive impact on composite reliability or AVE as prescribed by Hair et al. [87].

4.1.3. Discriminant validity

An unobservable variable's discriminant validity describes how different it is from other latent variables. A method of evaluating discriminant validity is the Fornell-Larcker criterion. The square root of each construct's AVE is projected to be greater when compared to the construct with the highest association. Henseler et al. [88] suggested the heterotrait-monotrait (HTMT) ratio of correlations as an alternate approach to gauging discriminant validity. A high HTMT value denotes a difficulty with discriminant validity. The cutoff value for conceptually linked structural models is 0.90, whereas it is 0.85 for constructs with conceptually separate structures [88]. Tables 4 and 5 show the Fornell-Larcker and HTMT ratio scores, indicating that all the values have met the minimum criteria except SEQ-PR (HTMT: 0.908).

4.2. Structural model assessment

The structural model describes the connections between the constructs. It is essential to determine whether there is any multicollinearity among the constructs before moving on to the next phase. The multicollinearity problem is measured using the VIF score. For each construct, the threshold value should be smaller than 5 to account for the absence of multicollinearity [87] The VIF scores for all the constructs are less than 5, as shown in Table 6, indicating no multicollinearity issues in the research framework.

4.2.1. Coefficient of determination (R^2)

When forecasting the result of an event, the coefficient of determination is a statistical measurement that looks at how changes in one variable may be explained by the difference in another. The R^2 value of behavioral intention to use fintech services 0.684 means PE, EE, SI, IQ, SQ, SEQ, and PR can explain 68.4 % of BI. Moreover, the R^2 score of AU is 0.362 means, BI can explain 36.2 % of AU. Fig. 2 shows the R^2 value.

Table 3
Cronbach's alpha and Composite Reliability Scores.

	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
AU	0.723	0.829	0.549
BI	0.814	0.890	0.729
EE	0.905	0.929	0.724
IQ	0.784	0.861	0.610
PE	0.882	0.918	0.738
PR	0.896	0.928	0.762
SEQ	0.879	0.917	0.734
SI	0.841	0.887	0.612
SQ	0.736	0.850	0.655

Table 4
Fornell-Larcker scores.

	AU	BI	EE	IQ	PE	PR	SEQ	SI	SQ
AU	**0.741**								
BI	0.602	**0.854**							
EE	0.433	0.698	**0.851**						
IQ	0.500	0.711	0.690	**0.781**					
PE	0.363	0.587	0.726	0.586	**0.859**				
PR	0.532	0.691	0.610	0.653	0.518	**0.873**			
SEQ	0.522	0.747	0.696	0.720	0.594	0.810	**0.857**		
SI	0.534	0.638	0.613	0.617	0.522	0.616	0.661	**0.782**	
SQ	0.448	0.668	0.631	0.585	0.559	0.555	0.640	0.569	**0.809**

Table 5
HTMT scores.

	AU	BI	EE	IQ	PE	PR	SEQ	SI	SQ
AU									
BI	0.782								
EE	0.530	0.811							
IQ	0.657	0.878	0.805						
PE	0.448	0.686	0.811	0.694					
PR	0.655	0.803	0.673	0.767	0.574				
SEQ	0.654	0.883	0.777	0.862	0.671	0.908			
SI	0.686	0.765	0.696	0.758	0.597	0.713	0.771		
SQ	0.614	0.863	0.771	0.755	0.687	0.680	0.795	0.725	

Table 6
VIF scores.

	VIF
AU1	1.181
AU2	1.569
AU3	1.734
AU4	1.440
BI1	1.929
BI2	1.906
BI3	1.632
EE1	2.594
EE2	2.387
EE3	2.596
EE4	2.403
EE5	2.389
IQ1	1.822
IQ2	1.998
IQ3	1.259
IQ4	1.658
PE1	2.234
PE2	2.437
PE3	2.242
PE4	2.208
PR1	2.804
PR2	2.938
PR3	2.138
PR4	2.401
SEQ1	2.289
SEQ2	2.283
SEQ3	2.499
SEQ4	1.995
SI1	1.978
SI2	2.211
SI3	1.449
SI4	1.884
SI5	1.858
SQ1	1.390
SQ2	1.555
SQ3	1.466

4.2.2. Path co-efficient

The bootstrapping method was used in this study to determine the significance of the path coefficient. The path coefficient values used to test the study's hypotheses and findings are shown in Table 7. If the p-value is less than 0.05, the hypothesis is accepted. Hypotheses H2, H4, H5, H6, H7, and H8 are accepted based on the data in Table 7 since the p-value was less than 0.05. However, hypotheses H1 and H3 are rejected as the p-value is more than 0.05. Also, this outcome shows that SQ has the highest impact, followed by IQ, SEQ, EE, and PR on BI.

4.3. Discussion

The Malaysian insurance and Takaful industry are evolving quickly. More consumers are requesting improved digital solutions while asking questions about life and health insurance protection as the world navigates the epidemic, especially in health and safety. In the centuries-old insurance business, digitalization has encouraged incumbent insurers to collaborate more closely with technologies like fintech or insurtech [89].

The study investigated the factors influencing customers to accept fintech services in the Malaysian insurance and takaful industry. The study proposed eight hypotheses based on the literature review, and six were accepted.

Hypothesis 1 of the study proposed that PE positively influences BI. However, the results from Table 7 showed that PE ($\beta = 0.019$; t-value = 0.363; p-value = 0.717) has no impact on the BI of customers. The result is like the earlier studies [90]. One of the causes would be that more individuals are becoming technologically literate, particularly in light of the internet's recent popularity surge and user base. So, the insurance and takaful industry customers do not feel that using a fintech platform for insurance-related activities will make any difference. This result differs from most technology adoption studies [91].

The second hypothesis tested the impact of EE on BI. The results showed that EE ($\beta = 0.153$; t-value = 2.259; p-value = 0.024) significantly influences BI. A similar result is found in the earlier literature [92,93]. This indicates that Malaysian consumers in the insurance and takaful industries think using FinTech applications is simple, easy to grasp, and free of effort. Easy-to-use apps motivate consumers to perform insurance activities in the fintech platforms.

The third hypothesis stated that SI has a positive impact on BI. However, the hypothesis got rejected, and the result revealed that SI ($\beta = 0.089$; t-value = 1.801; p-value = 0.072) has no impact on BI. The result is consistent with prior studies [71,94]. That means others do not influence consumers using any fintech platform for insurance-related transactions. The reason may be due to the security concern and privacy of the apps. Consumers feel afraid of third-party fintech apps because of the possibility of scams. So, individuals

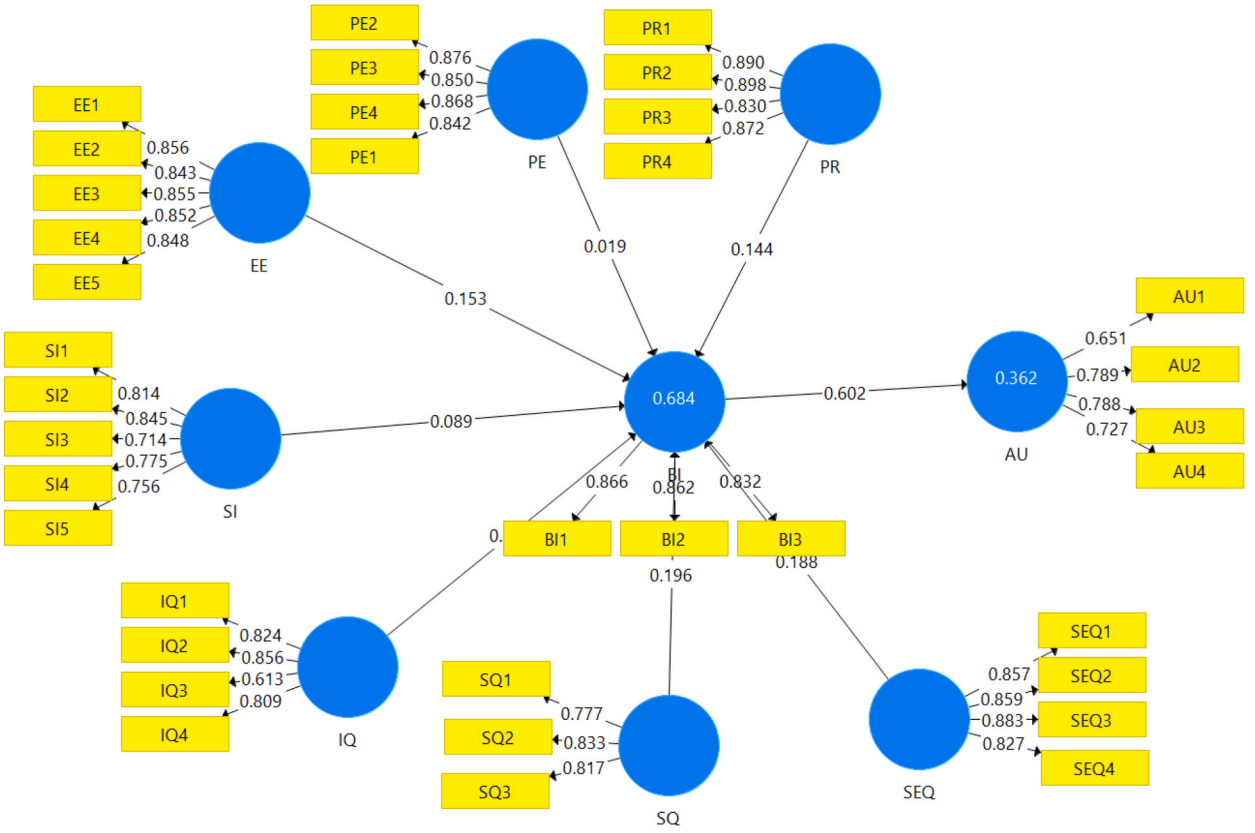

Fig. 2. R^2 value.

Table 7
Path Co-efficient values.

	Original Sample, β	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
BI - > AU	0.602	0.602	0.038	15.899	0.000
EE - > BI	0.153	0.155	0.068	2.259	0.024
IQ - > BI	0.194	0.192	0.061	3.196	0.001
PE - > BI	0.019	0.024	0.054	0.363	0.717
PR - > BI	0.144	0.147	0.069	2.100	0.036
SEQ - > BI	0.188	0.184	0.076	2.490	0.013
SI - > BI	0.089	0.089	0.05	1.801	0.072
SQ - > BI	0.196	0.193	0.049	4.034	0.000

personally decide whether to use the fintech platform or not.

Hypotheses four, five and six state the impact of the quality dimensions IQ, SQ, and SEQ on BI. According to Table 7 and IQ (β = 0.194; t-value = 3.196; p-value = 0.001), SQ (β = 0.196; t-value = 4.304; p-value = 0.000) and SEQ (β = 0.188; t-value = 2.490; p-value = 0.013) showed a significant positive impact on BI to use fintech for insurance-related transactions. The findings align with the results of earlier studies where all the quality dimensions showed a positive impact [95,96]. A high level of intention to use the fintech system for insurance activity is caused by information quality that is accurate, complete, timely, relevant, and trustworthy and that meets the needs of consumers. In addition, Malaysian insurance industry customers believe that the fintech platform's system quality is adaptable, boosting productivity, improving decision-making, and reducing the time and effort needed to complete tasks like conducting insurance transactions. Moreover, the service quality of the insurance companies to help with fintech services mitigate the uncertainty of using the fintech platforms for insurance-related purposes.

Hypothesis seven tested the impact of PR on BI. The findings showed that PR (β = 0.144; t-value = 2.100; p-value = 0.036) significantly negatively impacts BI to use fintech services. The result is consistent with earlier studies [16,97]. The possible reason is that insurance industry customers who intend to use Fintech services are more conscious of risk factors and show less trust if they perceive a higher level of risk in financial Fintech transactions. Moreover, hypothesis eight verified the impact of BI on AU. The result indicates that BI (β = 0.602; t-value = 15.899; p-value = 0.000). The result is similar to the studies [71,98]. That means a higher intention to use fintech services higher possibility of insurance customers using fintech platforms for insurance activities.

5. Conclusion

The insurance industry is being disrupted by the growth of fintech, shifting customer behavior, and cutting-edge technologies. Fintech technologies can bring about a variety of advantages, including increased financial inclusion, cost savings, improved risk assessment, and efficiency gains in the insurance industry. However, implementing fintech technologies in the insurance and takaful industry is at the initial stage in Malaysia. To foster the insurance industry's growth through fintech inclusion, it is essential to understand the dominant factors influencing customers to accept fintech services. The study aims to identify the factors that influence Malaysian insurance and takaful industry customers to accept fintech services. The study integrated two well-established technology adoption models: UTAUT and Delone and Mclean IS success. The study proposed that PE, EE, SI, IQ, SQ, SEQ, and PR are the indicators that can influence the customers' fintech acceptance. Structural equation modeling was used to analyze the data collected from the insurance industry customers to facilitate the study. The result of the study revealed that EE, IQ, SQ, SEQ, and PR significantly positively impact behavioral intention to use fintech services, where SQ showed the highest impact. In addition, BI has a significant positive influence on the actual use of fintech services. However, PE and SI showed no impact. The study results and framework will help academicians and researchers for further studies in fintech adoption. Moreover, the result will help the insurance and takaful companies, fintech firms, and government regulatory bodies to take necessary steps to improve the efficiency and profitability of the insurance and takaful industry using fintech services.

5.1. Theoretical contribution

Firstly, previous research in the fintech domain has predominantly focused on UTAUT2 within areas like mobile banking, mobile fintech, crowdfunding, and blockchain. Although there are some researches that used the D & M Information Success Model for mobile banking, there has been a noticeable gap in using the D & M model in the prior literature when it comes to examining fintech adoption by customers in conjunction with UTAUT2. In this study, we address this gap by integrating two prominent models in technology adoption including UTAUT2 and the D & M Information System Model focusing on user perspectives and quality dimensions. Consequently, we make a valuable contribution to the existing fintech literature by extending the theoretical framework, thereby providing an integrated research framework that lays the foundation for future studies in the fintech field.

In addition, given the rising concerns regarding the security of financial technology, this research validates the effect of users' perceptions of perceived risk and intentions to adopt fintech services. Consequently, this study advances the comprehension of the role of perceived risk. By doing so, the study enriches the existing fintech literature by shedding light on the role of perceived risk in understanding customer adoption of fintech.

Moreover, this is one of the pioneering studies focusing on fintech services acceptance in the insurance industry. Prior studies on fintech adoption are mainly focused on the banking, SME, etc. industry. The study's theoretical framework will help the academicians

to further investigate the fintech adoption in the insurance industry in other geographical contexts.

5.2. Managerial implications

The study result will help Malaysia's insurance and takaful companies understand customer needs because technological advancements and shifting customer expectations are driving innovation in the insurance sector. In addition, the fintech companies are required to fulfil the requirements set by the insurance companies. Fintech firms need to develop user-friendly apps and maintain good information quality, system quality and service quality for insurance and takaful companies so that the customers feel comfortable and impactful while using the fintech platform. Moreover, regulators must consider how financial technology may affect consumer protection and how clients are treated fairly.

5.3. Limitations and future studies

The study has several limitations. The primary limitation of the study is the small sample size. This may restrict the generalizability of the research findings across Malaysia's various demographic groups. However, the sample size has met the minimum requirement set by Barclay et al. (1995). The study used two technology adoption models, UTAUT2 and Delone & Mclean. The model can only explain 68.4 % of BI and 36.2 % of AU. Future studies can include more variables from the technology adoption literature to increase the coefficient of determination values. In addition, moderating variables like age, gender, experience, trust, and perceived credibility can be used in future fintech adoption studies.

Funding statement

The research project was funded by Research Management Center of Universiti Malaysia Perlis, Special Grant Number: 9004-00092.

Data availability statement

Data included in article.

CRediT authorship contribution statement

Md Sharif Hassan: Conceptualization, Formal analysis, Investigation, Writing – original draft, Methodology. **Md Aminul Islam:** Funding acquisition, Methodology, Supervision, Writing – review & editing. **Mohd Faizal bin Yusof:** Formal analysis, Resources, Validation, Writing – original draft. **Hussen Nasir:** Data curation, Project administration, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2023.e21130.

Appendix

Measurement Items	References
Performance Expectancy	
PE1: Using fintech services helps me to accomplish insurance-related transactions more quickly.	Rahim et al. (2022) [25]
PE2: Using fintech services increases my productivity in insurance policy handling.	
PE3: Using fintech services makes it easier for me to do insurance-related transactions (i.e., premium payment, loan payment)	
PE4: Using fintech services improves my overall insurance-related transaction performance.	
Effort Expectancy	
EE1: I find the fintech services platform easy to use.	Rahim et al. (2022) [25]
EE2: My interaction with the fintech services platform is clear and understandable	
EE3: It is easy for me to become skillful at using the fintech services platform	
EE4: I find the fintech services platform flexible to interact with	
Social Influence	

(*continued on next page*)

(*continued*)

Measurement Items	References
SI1: People who are important to me expect me to use fintech services to perform insurance-related transactions.	Al-Nawaseh (2020) [35], and Chan et al. (2022) [73]
SI2: Those people that influence my behavior think that I should use fintech services to conduct insurance policy payments.	
SI3: I will use fintech services for insurance premium payments if people in my community widely use the service	
SI4: I expect using fintech services to be trendy	
SI5: I think that using fintech services would make me look professional in managing my insurance policy	
Information Quality	
IQ1: The information provided by the fintech platform benefits insurance transactions.	Tam and Oliveira (2016) [74]
IQ2: The insurance information provided by the fintech platform is understandable.	
IQ3: The insurance information provided by the fintech platform is interesting	
IQ4: The insurance information is reliable in fintech platform.	
System Quality	
SQ1: Fintech services are well structured for insurance services	Tam and Oliveira (2016) [74]
SQ2: Fintech services allow finding insurance information effortlessly.	
SQ3: Fintech services are easy to navigate.	
Service Quality	
SEQ1: The service provider is always willing to help whenever I need support with the fintech services.	Tam and Oliveira (2016) [74]
SEQ2: The service provider provides personal attention when I experience problems with the fintech services.	
SEQ3: The service provider provides services related to fintech at the promised time.	
SEQ4: The service provider has enough knowledge to answer my questions concerning fintech.	
Perceived Risk	
PR1: Using Fintech services is associated with a high level of risk.	Kim et al. (2009) [75]
PR2: There is a high potential for loss in using fintech services	
PR3: There is considerable risk involved in using fintech services	
PR4: A decision to use fintech services are risky	
Behavioral Intention to Use	
BI1: If I have used Fintech services for insurance-related activities and transactions, I am willing to continue using them.	Hu et al. (2019) [76]
BI2: I want to use Fintech services soon for insurance-related activities and transactions.	
BI3: I will recommend Fintech services to my friends for insurance-related activities and transactions	
Actual Usage	
AU1: I sometimes use fintech services to conduct insurance transactions.	Gupta and Arora (2020) [77]
AU2: I often use fintech services to conduct insurance transactions.	
AU3: I regularly use fintech services to conduct insurance transactions.	
AU4: I always use fintech services to conduct insurance transactions.	

References

[1] K. Gai, M. Qiu, X. Sun, A survey on FinTech, J. Netw. Comput. Appl. 103 (2018 Feb 1) 262–273, https://doi.org/10.1016/j.jnca.2017.10.011.

[2] C. Pazarbasioglu, A.G. Mora, M. Uttamchandani, H. Natarajan, E. Feyen, M. Saal, Digital Financial Services, vol. 54, World Bank, 2020.

[3] D. Grinberg, FinTech for Insurance: How Technology Is Disrupting the Insurance Industry, Tech Magic, 2023. Available at: https://www.techmagic.co/blog/fintech-insurance/#:~:text=It%20encompasses%20using%20digital%20platforms,customer%20experience%2C%20and%20risk%20assessment.

[4] O. Tennyson, O.E. Mercy, E-payment system and its sustainable development in the Nigerian economy, Eur. J. Bus. Manag. 6 (2014) 48–56.

[5] Acko Digital Insurance, Insights on Digital Trends in Insurance Industry, 2021. November). Available at: https://www.acko.com/digital-insurance-trends-and-benefits/.

[6] D. Jung, V. Dorner, F. Glaser, S. Morana, Robo-advisory: digitalization and automation of financial advisory, Bus. Info. Syst. Eng. 60 (2018 Feb) 81–86, https://doi.org/10.1007/s12599-018-0521-9.

[7] EY Global Financial Services, Global FinTech Adoption Index 2019, 2019. Available at: https://assets.ey.com/content/dam/ey-sites/ey-com/en_gl/topics/banking-and-capital-markets/ey-global-fintech-adoption-index.pdf.

[8] Asia Insurance Review. Insurance Directory of Asia 2022, 2022. Available at: https://apps.asiainsurancereview.com/IDA/Asp/CompanyList.aspx?company=&type=&jobType=Insurers&country=Malaysia&search=company&pagin=4. (Accessed 23 September 2022).

[9] Atlas Magazine, Malaysian Takaful Insurance Market in the First Half of 2021, 2021. December. Available at: https://www.atlas-mag.net/en/article/malaysian-takaful-insurance-market-in-the-first-half-of-2021. (Accessed 23 September 2022).

[10] Fintech News Malaysia, Fintech Malaysia Report 2021 – Fintech Reaches an Inflection Point in Malaysia, 2021 April. Available at: https://fintechnews.my/27070/malaysia/fintech-malaysia-report-2021/. (Accessed 23 September 2022).

[11] UOB, Shifting Consumer Habits Drive Malaysia FinTech Growth, 2022 April. https://www.uobgroup.com/techecosystem/news-insights-consumer-research-malaysia.html.

[12] PWC, Catching the Fintech Wave: A Survey on Fintech in Malaysia, 2016 November. Available at:.

[13] R. Hasan, M. Ashfaq, L. Shao, Evaluating drivers of fintech adoption in The Netherlands, Global Bus. Rev. (2021 Aug 30), 09721509211027402, https://doi.org/10.1177/09721509211027402.

[14] M. Najib, W.J. Ermawati, F. Fahma, E. Endri, D. Suhartanto, Fintech in the small food business and its relation with open innovation, J. Open Innov.: Technol., Market, and Complex. 7 (1) (2021 Mar 8) 88, https://doi.org/10.3390/joitmc7010088.

[15] I.A. Oladapo, M.M. Hamoudah, M.M. Alam, O.R. Olaopa, R. Muda, Customers' perceptions of FinTech adaptability in the Islamic banking sector: comparative study on Malaysia and Saudi Arabia, J. Model. Manag. 17 (4) (2022 Nov 29) 1241–1261.

[16] M. Ali, S.A. Raza, B. Khamis, C.H. Puah, H. Amin, How perceived risk, benefit and trust determine user Fintech adoption: a new dimension for Islamic finance, foresight 23 (4) (2021 Jul 13) 403–420.

[17] J. Xie, L. Ye, W. Huang, M. Ye, Understanding FinTech platform adoption: impacts of perceived value and perceived risk, J. Theor. Appl. Electr. Commerce Res. 16 (5) (2021 Jun 17) 1893–1911.

[18] E. Sholihah, I.S.W. Antari, R.F. Rochimawati, Determinants of BSI mobile banking adoption intentions: DeLone & McLean and UTAUT Model integration with religiosity, Asian J Islamic Manag. (AJIM). (2023) 1–17.
[19] M.D. He, M.R.B. Leckow, M.V. Haksar, M.T.M. Griffoli, N. Jenkinson, M.M. Kashima, H. Tourpe, Fintech and financial services: initial considerations, 19 Sep, in: Staff Discussion Note 17/05., 2017 [Online] Available from: https://www.imf.org/~/media/Files/Publications/SDN/2017/sdn1705.
[20] M. Saal, S.K. Starnes, T. Rehermann, Digital Financial Services: Challenges and Opportunities for Emerging Market Banks. EM Compass Note, World Bank Group, 2017. Available from: http://documents.worldbank.org/curated/en/750421502949470705/Digital-financial-services-challenges-and-opportunities-for-emerging-market-banks.
[21] Manyika J, Lund S, Singer M, White O, Berry C. Digital finance for all: powering inclusive growth in emerging economies. McKinsey Report. [Online] Available from: https://www.mckinsey.com/~/media/mckinsey/featured%20insights/Employment%20and%20Growth/How.
[22] M.T. Le, Examining factors that boost intention and loyalty to use Fintech post-COVID-19 lockdown as a new normal behavior, Heliyon 7 (8) (2021), e07821.
[23] S. Singh, M.M. Sahni, R.K. Kovid, Exploring antecedents of FinTech adoption using adapted technology acceptance model, in: Advances in Systems Engineering, Springer, Singapore, 2021, pp. 337–352, https://doi.org/10.1007/978-981-15-8025-3_34.
[24] C.C. Jin, L.C. Seong, A.A. Khin, Factors affecting the consumer acceptance towards fintech products and services in Malaysia, Int. J. Asian Soc. Sci. 9 (1) (2019) 59–65.
[25] N.F. Rahim, M.H. Bakri, B.A. Fianto, N. Zainal, S.A. Hussein Al Shami, Measurement and structural modeling on factors of Islamic Fintech adoption among millennials in Malaysia, J Islamic Mark (2022). Ahead of print, https://doi-org.ezproxyunimap.idm.oclc.org/10.1108/JIMA-09-2020-0279.
[26] C. Tun-Pin, W.C. Keng-Soon, Y. Yen-San, C. Pui-Yee, J.T. Hong-Leong, N. Shwu-Shing, An adoption of fintech service in Malaysia, Southeast Asia J Contemp Bus 18 (5) (2019) 134–147.
[27] V. Sharma, D. Sood, Adoption of internet of things and services in the Indian insurance industry, in: Big Data: A Game Changer for Insurance Industry, Emerald Publishing Limited, 2022, pp. 35–42.
[28] W. Bian, T. Ge, Y. Ji, X. Wang, How Is Fintech Reshaping the Traditional Financial Markets? New Evidence from InsurTech and Insurance Sectors in China, China Econ Rev, 2023, 102004.
[29] V. Venkatesh, M.G. Morris, G.B. Davis, F.D. Davis, User acceptance of information technology: toward a unified view, MIS Q. (2003 Sep 1) 425–478.
[30] V. Venkatesh, J.Y. Thong, X. Xu, Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology, MIS Q. (2012) 157–178, https://doi.org/10.2307/41410412.
[31] H.A. Widyanto, K.A. Kusumawardani, A. Septyawanda, Encouraging behavioral intention to use mobile payment: an extension of Utaut2, Jurnal Muara Ilmu Ekonomi Dan Bisnis 4 (1) (2020) 87–97, https://doi.org/10.24912/jmieb.v4i1.7584.
[32] N. Araújo Vila, J.A. Fraiz Brea, J. Pelegrín Borondo, Applying the UTAUT2 model to a non-technological service: the case of Spa tourism, Sustainability 13 (2) (2021) 803, https://doi.org/10.3390/su13020803.
[33] F. Nikolopoulos, S. Likothanassis, Using UTAUT2 for cloud computing technology acceptance modeling, in: Proceedings of the Second International Conference on Internet of Things, Data and Cloud Computing, 2017 Mar, pp. 1–6, https://doi.org/10.1145/3018896.3025153.
[34] H. Khazaei, Integrating cognitive antecedents to UTAUT model to explain adoption of blockchain technology among Malaysian SMEs, JOIV: Int. J. Info. Visual. 4 (2) (2020) 85–90, https://doi.org/10.30630/joiv.4.2.362.
[35] M.K. Al Nawayseh, Fintech in COVID-19 and beyond: what factors are affecting customers' choice of fintech applications? J Open Innov: Technol, Mark, Complex 6 (4) (2020) 153, https://doi.org/10.3390/joitmc6040153.
[36] N. Khatun, M. Tamanna, Factors affecting the adoption of Fintech: a study based on the financial institutions in Bangladesh, Copernican J. Financ. Account. 9 (4) (2020) 51–75, https://doi.org/10.12775/CJFA.2020.021.
[37] K. Yohanes, K. Junius, Y. Saputra, R. Sari, Y. Lisanti, D. Luhukay, Unified Theory of Acceptance and Use of Technology (UTAUT) model perspective to enhance user acceptance of fintech application, in: 2020 International Conference on Information Management and Technology (ICIMTech), IEEE, 2020, pp. 643–648, https://doi.org/10.1109/ICIMTech50083.2020.9211250.
[38] S. Choi, The flipside of ubiquitous connectivity enabled by smartphone-based social networking service: social presence and privacy concern, Comput. Hum. Behav. 65 (2016) 325–333, https://doi.org/10.1016/j.chb.2016.08.039.
[39] K. Tamilmani, N.P. Rana, Y.K. Dwivedi, Use of 'habit' is not a habit in understanding individual technology adoption: a review of UTAUT2 based empirical studies, in: International Working Conference on Transfer and Diffusion of IT, Springer, 2018 Jun, pp. 277–294, https://doi.org/10.1007/978-3-030-04315-5_19.
[40] S.M. Sepasgozar, L.E. Bernold, Factors influencing construction technology adoption, in: 19th CIB World Building Congress, 2013 (Brisbane, Australia).
[41] W. DeLone, E. McLean, Information systems success: the quest for dependent variables, Inf. Syst. Res. 3 (1) (1992) 60–95.
[42] W.H. DeLone, E.R. McLean, The DeLone and McLean model of information systems success: a ten-year update, J. Manag. Inf. Syst. 19 (4) (2003) 9–30.
[43] J.H. Wu, Y.M. Wang, Measuring KMS success: a respecification of the DeLone and McLean's model, Inf. Manag. 43 (6) (2006) 728–739.
[44] Y.T. Prasetyo, A.K.S. Ong, G.K.F. Concepcion, F.M.B. Navata, R.A.V. Robles, I.J.T. Tomagos, et al., Determining factors affecting acceptance of e-learning platforms during the COVID-19 pandemic: integrating extended technology acceptance model and DeLone & McLean IS success model, Sustainability 13 (15) (2021) 8365, https://doi.org/10.3390/su13158365.
[45] C. Tam, T. Oliveira, Understanding mobile banking individual performance: the DeLone & McLean model and the moderating effects of individual culture, Internet Res. 27 (3) (2017) 538–562.
[46] B.M. Al-Ghazali, A.M. Rasli, R.M. Yusoff, A.Y. Mutahar, Antecedents of continuous usage intention of mobile banking services from the perspective of Delone and Mclean model of information system success, Int. J. Econ. Financ. Issues 5 (1) (2015) 13–21.
[47] M.M. Komba, P. Ngulube, An empirical application of the DeLone and McLean model to examine factors for e-government adoption in the selected districts of Tanzania, in: Emerging Issues and Prospects in African E-Government, IGI Global, 2015, pp. 118–129.
[48] E.L. Slade, M.D. Williams, Y.K. Dwivedi, Mobile payment adoption: classification and review of the extant literature, Market. Rev. 13 (2) (2013) 167–190.
[49] H. Bauer, S. Barnes, T. Reichardt, M. Neumann, Driving consumer acceptance of mobile marketing: a theoretical framework and empirical study, J. Electron. Commer. Res. 6 (3) (2005) 181–191.
[50] S. Alwi, R.M. Alpandi, S.H. Yusof, M. Nadia, M. Salleh, T.S. Peng, The evidence of industrial revolution 4.0 through the adoption of financial technology (FINTECH) during COVID-19 pandemic among Malaysians, Int. J. Mech. Eng. 7 (4) (2022) 125–131.
[51] K. Ghalandari, The effect of performance expectancy, effort expectancy, social influence and facilitating conditions on acceptance of e-banking services in Iran: the moderating role of age and gender, Middle East J. Sci. Res. 12 (6) (2012) 801–807.
[52] M. Tenk Tt, H.C. Yew, L.T. Heang, E-wallet Adoption: a case in Malaysia, Int J Res Commerce Manage Stud 2 (2) (2020) 216–233.
[53] S.T. Urus, F. Kurniasari, S.N. Faiza Syed Mustapha Nazri, P. Utomo, I.W. Othman, S.Y. Jimmy, N.A. Hamid, A comparative study of fintech payment services adoption among MALAYSIAN and Indonesian fresh graduates: through the lens of UTAUT theory, E. Eur. J. Enterprise Technol. 119 (13) (2022 Dec 5).
[54] D.G. Silva, C. Coutinho, C.J. Costa, Factors influencing free and open-source software adoption in developing countries—an empirical study, J Open Innov: Technol, Market, Complex 9 (1) (2023) 21–33, https://doi.org/10.1016/j.joitmc.2023.01.002.
[55] A. Abushakra, D. Nikbin, A. Odeh, R. Abdulwahab, The effect of trust, IT knowledge, and entrepreneur's innovativeness to embrace or shun the internet of things, Front. Psychol. 13 (2022 Nov 24), 1035015.
[56] Y.H. Chen, I. Chengalur-Smith, Factors influencing students' use of a library Web portal: applying course-integrated information literacy instruction as an intervention, Internet High Educ. 26 (2015) 42–55, https://doi.org/10.1016/j.iheduc.2015.04.005.
[57] Y.M. Huang, Y.H. Pu, T.S. Chen, P.S. Chiu, Development and evaluation of the mobile library service system success model: a case study of Taiwan, Electron. Libr. 33 (6) (2015) 1174–1192, https://doi.org/10.1108/el-06-2014-0094.
[58] S. Komiak, The effects of perceived information quality and perceived system quality on trust and adoption of online reputation systems, AMCIS 2010 Proc. (2010) 343. Available from: https://aisel.aisnet.org/amcis2010/343.

[59] Z. Wang, Z. Guan, F. Hou, B. Li, W. Zhou, What determines customers' continuance intention of FinTech? Evidence from YuEbao, Ind. Manag. Data Syst. 119 (8) (2019 Sep 19) 1625–1637.
[60] T. Ramayah, N.H. Ahmad, M.C. Lo, The role of quality factors in intention to continue using an e-learning system in Malaysia, Proc.-Soc. Behav. Sci. 2 (2) (2010 Jan 1) 5422–5426.
[61] M.K. Gharaibeh, N.K. Gharaibeh, An empirical study on factors influencing the intention to use mobile learning, Adv. Sci. Technol. Eng. Syst. J. 5 (5) (2020) 1261–1265.
[62] C. Grönroos, A service quality model and its marketing implications, Eur. J. Market. 18 (4) (1984) 36–44.
[63] E.M. Abu-Taieh, I. AlHadid, S. Abu-Tayeh, R.E. Masa'deh, R.S. Alkhawaldeh, S. Khwaldeh, A.A. Alrowwad, Continued intention to use of M-banking in Jordan by integrating UTAUT, TPB, TAM and service quality with ML, J. Open Innov.: Technol., Market, and Complex. 8 (3) (2022 Jul 13) 120.
[64] Z. Zahara, E. Rombe, N. Ngatimun, J. Suharsono, The effect of e-service quality, consumer trust, and social media marketing on intention to use online transportation services, Int J Data Network Sci 5 (3) (2021) 471–478.
[65] M.S. Featherman, P.A. Pavlou, Predicting e-services adoption: a perceived risk facets perspective, Int. J. Hum. Comput. Stud. 59 (4) (2003) 451–474.
[66] J. Hwang, J.Y.(J.) Choe, Exploring perceived risk in building successful drone food delivery services, Int. J. Contemp. Hospit. Manag. 31 (8) (2019) 3249–3269. https://doi-org.ezproxyunimap.idm.oclc.org/10.1108/IJCHM-07-2018-0558.
[67] K. Al-Saedi, M. Al-Emran, A systematic review of mobile payment studies from the lens of the UTAUT model, Recent Adv. Technol. Acceptance Models And Theor. (2021) 79–106.
[68] T.D. Nguyen, T.C. Nguyen, The role of perceived risk on intention to use online banking in Vietnam, in: 2017 International Conference on Advances in Computing, Communications and Informatics (ICACCI), IEEE, 2017 Sep, pp. 1903–1908.
[69] K.I. Lee, Understanding Taiwan seniors' motivation to consume food-away-from-home, J. Tourism Hospit. Manag. 4 (1) (2016) 22–36, https://doi.org/10.17265/2328-2169/2016.02.003.
[70] W.W. Zhu, J.C. Wei, D.T. Zhao, Anti-nuclear behavioral intentions: the role of perceived knowledge, information processing, and risk perception, Energy Pol. 88 (2016) 168–177, https://doi.org/10.1016/j.enpol.2015.10.009.
[71] P.K. Senyo, E.L. Osabutey, Unearthing antecedents to financial inclusion through FinTech innovations, Technovation 98 (2020), 102155, https://doi.org/10.1016/j.technovation.2020.102155.
[72] Q. Cao, X. Niu, Integrating context-awareness and UTAUT to explain Alipay user adoption, Int. J. Ind. Ergon. 69 (2019) 9–13, https://doi.org/10.1016/j.ergon.2018.09.004.
[73] R. Chan, I. Troshani, S. Rao Hill, A. Hoffmann, Towards an understanding of consumers' FinTech adoption: the case of Open Banking, Int. J. Bank Market. 40 (4) (2022) 886–917, https://doi.org/10.1108/IJBM-08-2021-0397.
[74] C. Tam, T. Oliveira, Understanding the impact of m-banking on individual performance: DeLone & McLean and TTF perspective, Comput. Hum. Behav. 61 (2016) 233–244.
[75] D.J. Kim, D.L. Ferrin, H.R. Rao, A trust-based consumer decision-making model in electronic commerce: the role of trust, perceived risk, and their antecedents, Decis. Support Syst. 44 (2) (2008) 544–564, https://doi.org/10.1016/j.dss.2007.07.001.
[76] Z. Hu, S. Ding, S. Li, L. Chen, S. Yang, Adoption intention of fintech services for bank users: an empirical examination with an extended technology acceptance model, Symmetry 11 (3) (2019) 340, https://doi.org/10.3390/sym11030340.
[77] K. Gupta, N. Arora, Investigating consumer intention to accept mobile payment systems through unified theory of acceptance model: an Indian perspective, South Asian J Bus Stud 9 (1) (2020) 88–114, https://doi.org/10.1108/SAJBS-03-2019-0037.
[78] M. Hassan, M. Islam, M.F.B. Yusof, H. Nasir, N. Huda, Investigating the determinants of islamic mobile FinTech service acceptance: a modified UTAUT2 approach, Risks 11 (2) (2023) 40, https://doi.org/10.3390/risks11020040.
[79] U. Sekaran, R. Bougie, Research Methods for Business: A Skill Building Approach, john wiley & sons, 2016 Jun 27.
[80] D. Barclay, C. Higgins, R. Thompson, The partial least squares (PLS) approach to causal modeling: personal computer adoption and use as an illustration, Technology Studies 2 (2): 285–309, Creativ. Innovat. Manag. 14 (2) (1995), 169175.
[81] P.M. Podsakoff, S.B. MacKenzie, J.Y. Lee, N.P. Podsakoff, Common method biases in behavioral research: a critical review of the literature and recommended remedies, J. Appl. Psychol. 88 (5) (2003) 879.
[82] Y. Kim, T. Roh, Preparing an exhibition in the post-pandemic era: evidence from an O2O-based exhibition of B2B firms, Technol. Forecast. Soc. Change 185 (2022 Dec 1), 122041.
[83] T. Roh, J. Seok, Y. Kim, Unveiling ways to reach organic purchase: green perceived value, perceived knowledge, attitude, subjective norm, and trust, J. Retailing Consum. Serv. 67 (2022 Jul 1), 102988.
[84] N. Kock, Common method bias in PLS-SEM: a full collinearity assessment approach, Int. J. e-Collaboration 11 (4) (2015 Oct 1), 1-0.
[85] M.K. Lindell, D.J. Whitney, Accounting for common method variance in cross-sectional research designs, J. Appl. Psychol. 86 (1) (2001) 114.
[86] J.F. Hair, J.J. Risher, M. Sarstedt, C.M. Ringle, When to use and how to report the results of PLS-SEM, Eur. Bus. Rev. 31 (1) (2019 Jan 14) 2–4.
[87] J. Hair, C.L. Hollingsworth, A.B. Randolph, A.Y. Chong, An updated and expanded assessment of PLS-SEM in information systems research, Ind. Manag. Data Syst. 117 (3) (2017 Apr 10) 442–458.
[88] J. Henseler, C.M. Ringle, M. Sarstedt, A new criterion for assessing discriminant validity in variance-based structural equation modeling, J. Acad. Market. Sci. 43 (2015 Jan) 115–135.
[89] V. Gomes, Insurance: insurance industry sees big shift; technology the catalyst. https://www.theedgemarkets.com/article/insurance-insurance-industry-sees-big-shift-technology-catalyst, 2022. (Accessed 7 March 2023).
[90] E. Purwanto, J. Loisa, The intention and use behavior of the mobile banking system in Indonesia: UTAUT Model, Technol Rep Kansai Univ 62 (6) (2020) 2757–2767.
[91] N.N. Win, P.P. Aung, M.T. Phyo, Factors influencing behavioral intention to use and use behavior of mobile banking in Myanmar using a model based on unified acceptance theory, Hum Behav Dev Soc 22 (1) (2021) 19–30.
[92] K. Bajunaied, N. Hussin, S. Kamarudin, Behavioral intention to adopt FinTech services: an extension of unified theory of acceptance and use of technology, J Open Innov: Technol, Mark, Complex 9 (1) (2023), 100010.
[93] F.A.B. Ramos, Accessing the Determinants of Behavioral Intention to Adopt Fintech Services Among the Millennial Generation [Doctoral Dissertation], Universidade Nova de Lisboa, 2017.
[94] I.M. Macedo, Predicting the acceptance and use of information and communication technology by older adults: an empirical examination of the revised UTAUT2, Comput. Hum. Behav. 75 (2017) 935–948.
[95] F.R. Chalik, T. Faturohman, Customer satisfaction of e-wallet user: an adoption of information system success model, Quant. Anal. Soc. Financ. Market Dev. 30 (2022) 61–83.
[96] I. Riantama, I.N. Suardhika, A. Yuesti, Financial technology application success in the 4.0 Era, Int. J. Psychosoc. Rehabil. 24 (9) (2020) 2948–2962.
[97] D.L. Marafon, K. Basso, L.B. Espartel, M.D. de Barcellos, E. Rech, Perceived risk and intention to use internet banking: the effects of self-confidence and risk acceptance, Int. J. Bank Market. 36 (2) (2018) 277–289.
[98] B. Rahardjo, B.M.B. Akbar, I. Novitaningtyas, The analysis of intention and use of Financial Technology, J Account Strat Finance 3 (1) (2020) 88–102.