Predicting the adoption of online insurance payment technology: The role of second-order trust

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Abstract

Purpose: Even though many life-insurance companies have created websites for clients, the acceptability of technological innovation is still low. We assessed the unified theory of acceptance and use of technology (UTAUT) in an online insurance payment technology (OIPT) system. The model was expanded to incorporate trust, which we believed would be involved in customer intent to utilize an online platform. The current study investigates the extent to which trust influences behavioral intention directly and indirectly

Design/methodology/approach: A cross-sectional survey approach was used to investigate the links between trust and behavioral intention to adopt OIPT. An online survey was used to obtain 210 valid responses from respondents in the Greater Jakarta area. Partial least squares (PLS) modeling was used to assess the measurement and structural models. High-order construct (HOC) Trust is funneled into a lower-order construct (LOC) defined by adequate theories: trust in technology and trust in life insurance's brand intimacy. This reduces the overall complexity of the study model, allowing for better interpretable output and easier to apprehend

Findings: The results provided support for four hypotheses: HOC trust has a positive effect on behavioral intention to use OIPT. Effort expectancy has the highest mediating effect in the relationship between HOC trust on Behavioral intention. Trust in technology has a better total effect compared to Trust in a brand (intimacy).

Research limitations/implications: This study was conducted in a specific are, Great Jakarta in Indonesia. Most responses were obtained from male (64%) and age above 50 years old (46%). Among of them (20%) are government employee. Thus, generation, gender and culture may bias our conclusions about the behavioral intention to use online payment in website. Therefore, it is advisable to exercise caution when extrapolating our findings to policyholders/insureds from private companies, or could obtained more respondents from, millennials generation, and career women, since these age groups have been known to display different behaviors and career woman may give different perspective about emotional trust.

Practical implications: Practically, these results suggest that the use of extended UTAUT using HOC Trust operationalized as a reflective-formative measure can have utility for management and system design. The total effect of LOC Trust in technology is high compared to LOC Trust in Brand intimacy, and effort expectancy is the best mediator in the model. We

drew on the findings of this study to inform the technology implementation strategy within insurance companies to make their website user-friendly, reliable, and operate in a truthful manner
Originality/value: The originality and novelty of this study Firstly, this study uses HOC Trust as a predictor of behavioral intention to use websites in the life insurance context in developing countries. Secondly, this study provides the result of a reflective formative second-order construct of trust as exogenous variables in the UTAUT model, and it is expected to be an alternative for future research in understanding of consumer trust in the successful implementation of life insurance websites. Thirdly, this study provides results of the mediating effect of performance expectancy, effort expectancy, and social influence as a consequence of additional trust as an exogenous construct in the model.

Keywords: UTAUT extension model, Behavioral intention, Higher order construct, Trust, Life insurance

Introduction

The COVID-19 pandemic has led to an increased need for life insurance and the introduction of a novel business model that employs video conferencing and e-signatures for a streamlined process. The Indonesian Finance Regulator (OJK) has ratified a regulation enabling the procurement of life insurance policies through a website to purchase and pay premiums conveniently. Online insurance policies usually have an option to submit claims online. This convenient process leads to a shorter overall timeframe from the submission of the claim until the insurance company's payment.

Despite significant efforts in the life insurance industry to shift away from the traditional agent-centered model towards website payment technology, the market continues to favour the conventional face-to-face approach. This indicates a preference for human relationships in establishing confidence when purchasing life insurance online. According to a 2020 survey conducted by the Life Insurance Marketing and Research Association (LIMRA) and the Boston Consulting Group (BCG), personal selling is the preferred method, and trust is one of the top three factors contributing to the safe completion of transactions when purchasing life insurance from websites. In contrast to other financial products, insurance products require adequate development and provision of services. (Lim, Hur, Lee, & Koh, 2009). This differentiates them from other financial products. The majority of life insurance policies are term policies and are subject to financial responsibility. (Pinquet, Guillén, & Ayuso, 2011). Careful thinking is necessary before acquiring life insurance policies because of its long-term feature. In their study, Naidu and Paramasivan (2015), discovered the lack of policy documentation or the obfuscation of its content was an obstacle to the ability of the majority of life insurance companies to influence customer behaviour online.

According to Davis (1989), user acceptability is essential for the successful adoption of any information technology (IT) or information system (IS) The technology acceptance model (TAM) is one of the most often recognized frameworks in the world of IT and ISs (Chauhan & Jaiswal, 2016); (Cimperman, Brenčič, & Trkman, 2016; Šumak & Šorgo, 2016). However, some researchers (Sánchez-Prieto, Olmos-Migueláñez, & García-Peñalvo, 2016; Šumak, Pušnik, Heričko, & Šorgo, 2017; Tsai, Chao, Lin, & Cheng, 2018) argue that the TAM has several flaws. These include the following: (1) not giving enough attention to how people view novel systems; (2) not paying enough attention to its indicators in favor of the external variables of perceived usefulness (PU) and perceived ease of use (PEOU); and (3) not paying enough attention to the connection between usage intention and usage attitude.

In their quest to solve the shortcomings of the TAM and create a more comprehensive IT acceptance model, Venkatesh, Morris, Davis, and Davis (2003) proposed the unified theory of acceptance and use of technology (UTAUT) model, which was first introduced and has been widely used for system utilization prediction and technology adoption/usage decisions in a variety of sectors. Scholars have obtained empirical support for the UTAUT model across contexts including radiological departments (Duyck et al., 2008), Enterprise Resource Planning (ERP) software (Chauhan & Jaiswal, 2016), interactive whiteboards (Šumak et al., 2017; Šumak & Šorgo, 2016), mobile health (Hoque & Sorwar, 2017), near-field communication technology (Khalilzadeh, Ozturk, & Bilgihan, 2017), health services (Cimperman et al., 2016), and classroom (Straub, 2009). The diversity of applications supports the proposition that the UTAUT might be suitably employed to predict customers' adoption of online insurance payment technology (OIPT).

Despite being widely used, the UTAUT model has drawn criticism and there are questions about its capacity to explain people's acceptance of technology. Van Raaij and Schepers (2008) have characterized the multiple conception of UTAUT categories as too complex and difficult to measure individual components. This empirical approach is made more complex by the need for moderating factors to obtain the high R2 that Venkatesh et al. (2003) reported (Van Raaij & Schepers, 2008). As a result, the UTAUT model has been expanded upon. According to several studies (Martins, Oliveira, and Popovič (2014); Maillet, Mathieu, and Sicotte (2015); Cimperman et al. (2016);Kabra, Ramesh, Akhtar, and Dash (2017);Khalilzadeh et al. (2017)), this model's capacity to forecast IT adoption may be improved by including more external factors.

In addition to the original UTAUT model, a number of factors have been suggested (e.g., self-efficacy, trust, habits, satisfaction, and perceived risk). To assess the variables influencing users' behavioural intents to use IT, Kabra et al. (2017) included personal innovation unique to IT and trust into the UTAUT model. Self-efficacy, risk, trust, security, and attitude were all considered by Khalilzadeh et al. (2017) in their analysis of the variables influencing users' behavioural intents to make mobile payments. Previous research on websites and mobile technologies has shown that users' behavioral intentions to embrace technology are significantly influenced by trust (Alalwan, Dwivedi, & Rana, 2017; Chao, 2019; Khalilzadeh et al., 2017)

Despite the substantial role of trust in influencing behavioral intention, research on purchasing and pay a premium of life insurance through websites using trust as an exogenous formative higher-order construct in the UTAUT model is limited. To address this research gap, this research investigates the following questions; (1) how does trust as a higher-order construct influence behavioral intention and different predictors of behavioral intention to use OIPT (2) what constructs give the best mediating effect to behavior intention to use OIPT (3) what element of the lower order trust give the best influence in behavioral intention to use OIPT.

The adoption of technology concerning online insurance payment technology (OIPT) systems has received little research attention. Our study extends previous research on the use of trust by examining trust as a higher-order construct that influences behavioural intentions both directly and indirectly through performance expectancy, effort expectancy, and social influence as mediators. The extended model was subsequently tested empirically. The aim of the study was threefold: firstly, to evaluate the implementation of the established theory of UTAUT, which predicts performance expectancy, effort expectancy, and social influence, as well as trust as a predictor of behavioral intention. Secondly, we investigated the role of performance expectation, effort expectancy, and social influence as mediators between trust and behavioral intention to use OIPT. Thirdly, the study treats trust as a formative higher-order construct, while investigating the influence of two lower first-order constructs on behavioral intention. This distinct analysis constitutes a unique aspect of the research.

Literature Review

In this section, we revisit UTAUT and its extension and discuss prior studies related to the adoption of online insurance payment technology and the role of trust in UTAUT framework

UTAUT and extension of Trust

Venkatesh et al. (2003) defined the UTAUT framework as having four antecedents: performance expectancy, effort expectancy, social influence, and enabling factors. These factors, when combined, have been found to explain up to 70% of the pooled variance in behavioural intention to employ a technical breakthrough (Venkatesh et al., 2003). Performance expectancy was developed by fusing notions of perceived utility, extrinsic motivation, job fit, relative advantage, and outcome expectancies. (Venkatesh et al., 2003). This concept is defined as the conviction that implementing a certain invention will result in favourable consequences. According to the technological adoption paradigm, performance expectation is equivalent to perceived usefulness (Nov & Ye, 2009; Van Raaij & Schepers, 2008). Effort expectancy, theoretically comparable to perceived ease of use in technology acceptance model Van Raaij and Schepers (2008), and it is defined as a user's subjective evaluations of ease of engaging with an IT system (Nov & Ye, 2004; (Venkatesh et al., 2003). Sub-components of this construct include perceptions of system ease of use and complexity (Venkatesh et al., 2003). Social influence is defined as the extent to which important others are perceived to support the user's intention to adopt an IT innovation (Venkatesh et al., 2003).

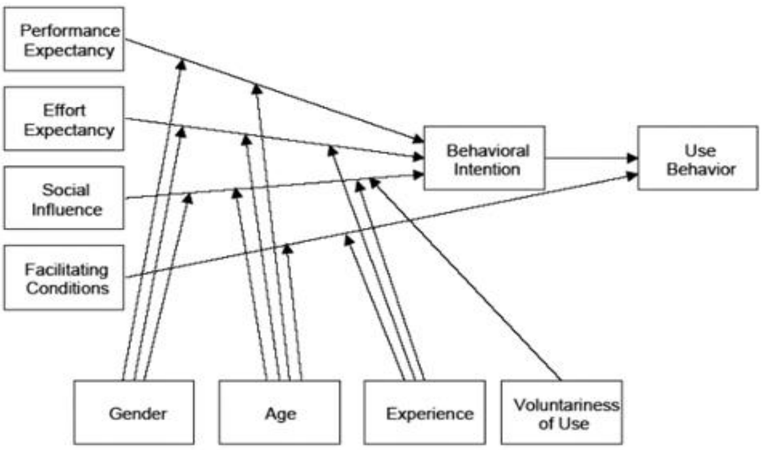

Figure 1. UTAUT Model
Source: (Venkatesh et al., 2003)

The role of social influence on behavioral intentions to use technology is unresolved. The research on change management indicates that successful technology adoption is influenced by peers and management (Amoako-Gyampah & Salam, 2004; J. S. Luo, Hilty, Worley, & Yager, 2006). Although some research shows a considerable effect on behavioural intention, there is mixed evidence supporting the exclusion of this factor in the UTAUT model. Gupta, Dasgupta, and Gupta (2008); Venkatesh et al. (2003) and others have reported a non-significant relationship (Anderson et al.,2006).

The construct of facilitating conditions is the final component of the UTAUT model, is described as the degree of accessibility to organizational and technological resources that make using the IT system easier. It encapsulates perceived behavioural control from the TPB. (Venkatesh et al., 2003). In previous research, the effect of facilitating conditions on intention over and above effort expectancy was non-significant (Venkatesh et al., 2003). Consequently, facilitating conditions has been incorporated within the UTAUT as a direct determinant of actual use (Venkatesh et al., 2003). This was not considered in our model. We suggest that UTAUT be broadened to encompass a greater variety of factors that influence behavioural intention to utilize online insurance payment technology both directly and indirectly. This is particularly relevant for integrated technologies such as document sharing, video conferencing during the application process, and premium payment using technology.

Despite the fact that the UTAUT model has been widely used, questions remain about its capacity to explain individual technology acceptance. Consequently, the original UTAUT model has been the subject of extensions. Many researchers (Alalwan, Dwivedi, Rana, & Algharabat, 2018; Chao, 2019; Kabra et al., 2017; Khalilzadeh et al., 2017) have suggested that increasing the number of external variables can enhance this model's ability to predict the acceptance of IT which cannot all fit in constructs of current UTAUT model. Trust appears to be positively related to the inclination to do internet transactions. The significant impact of trust on behavioral intentions has been confirmed by a number of studies (Alam, Hu, Kaium, Hoque, & Alam, 2020; Chao, 2019; Jang, Kim, & Lee, 2016; Papa, Mital, Pisano, & Del Giudice, 2020; Sarkar, Chauhan, & Khare, 2020). Alharbi (2014) included trust to evaluate users' behavioural intentions to adopt cloud services, and also Arfi, Nasr, Kondrateva, and Hikkerova (2021) incorporated trust to evaluate users' behavioural intention to use the IoT in eHealth. Furthermore, according to previous study on mobile technologies (Alalwan et al., 2017; Khalilzadeh et al., 2017) trust is a crucial factor determining users' behavioural intentions to adopt mobile technology. For example, Chao (2019) incorporated trust to analyse factors that influence users' behavioural intentions to use m-learning. Khalilzadeh et al. (2017) included trust, to evaluate the factors that influence users' behavioural intentions to make mobile payments.

Extension of UTAUT in life insurance industry

Trust in technology is especially applicable to situations requiring the use of an innovation that relies heavily on man-machine interfaces ((Lippert & Ojumu, 2008)). On the other hand, (Zhao, Zhao, Yuan, & Zhou, 2018) opined that aptitude, kindness and reliability are vital predecessor issues that influence a person's payment decision and use of the online platform. Likewise, the reputation of the insurance industry has a direct and significant influence on the intention to purchase life insurance products (Helmi, 2014).

In the context of life insurance industry, to purchase and pay premium using technology, trust is unquestionably a powerful influencing factor. Several researchers (Jiang, Liu, Liu, & Xiang, 2019; Mazuri, Samar, & Fatin Jamilah, 2017; Panigrahi, Azizan, & Waris, 2018) have also noted that trust plays a crucial role in determining behavioural intentions. Jiang et al. (2019), developed a theoretical model based on the UTAUT by adding online trust and perceived risk as external factors to identify significant factors that facilitate or hinder the purchase intention of online life insurance in China. The study's findings show that trust directly affects online life insurance purchasing intention, the more trust consumers have in the online market, the more likely they are to buy life insurance via the internet. de Andrés-Sánchez, González-Vila Puchades, and Arias-Oliva (2021) incorporated trust and moderating variables to analyse factors that influence users' behavioural intentions to use chatbot in life insurance industry. The result revealed that trust has a significant and positive impact on behavioural intention. However, their findings suggest that chatbot development for managing existing policies, especially in areas like claims, is not mature enough. This may account for the reluctance of surveyed policyholders to accept support from conversational bots, as they demonstrate low effort expectancy and trust ratings.

The Second Order of Trust

Trust is crucial in business interactions, especially where there is risk, ambiguity, or reliance. Researchers have recognized trust as a critical aspect in the success of e-commerce, despite the fact that several definitions exist. Few scholars, however, have taken a more direct approach, aiming to integrate the diverse varieties of trust into a cohesive collection of constructs that incorporate their multiple meanings. X. Luo, Li, Zhang, and Shim (2010), operationalized trust in a multi dimension construct in the context of mobile banking, based on the trust topology: disposition to trust, structural assurance, and trust belief (McKnight & Chervany, 2001). Disposition to trust, from the perspective of trust attributes, is defined as a general inclination in which people show faith or belief in humanity and adopt a trusting stance toward others [65]. Disposition to trust is people's general tendency to trust others and can be considered one type of personal trait. Structural assurance is the trust perception about the institutional environment. In the context of mobile banking, Structural assurance is the perception about the availability of the necessary legal and technical structures such as encryption, promises/guarantees, insurances, regulations, or other procedures in the wireless Internet to ensure the successful completion of financial transactions with a bank.

Trust belief is the perception that the trustworthiness of the vendor consists of a set of specific beliefs about integrity, benevolence, and competence (McKnight & Chervany, 2001). Contrary, X. Luo et al. (2010) the hypothesis of trust beliefs toward a bank will have a positive effect on consumers' behavioural intention to adopt mobile banking did not supported. The other two variable of trust was not conceptualized to have a direct impact to behavioural intention to adopt mobile banking.

In this study, we define trust based on social exchange theory (SET), the literature on trust has distinguished between two types of trust: emotional trust and cognitive trust (McAllister, 1995). Cognitive trust refers to the rational evaluation of whether the other party to tan exchange is trustworthy based on the knowledge and information's regarding its ability, professionalism and reliability (Chen et al., 2021; McAllister, 1995; Su & Mattila, 2020). Affective trust refers to the emotional bonds or connections with the party to the exchange that are grounded in the care and concerns that it demonstrates (McAllister, 1995). Affective or emotional trust is rarely addressed in human-technology interactions; nonetheless, emotions are recognized to greatly influence human trusting behaviour (Hoff & Bashir, 2015). The propensity of an individual to be sensitive to a technology based on the individual's expectations that the technology is predictable, reliable, and valuable is referred to as trust in technology (Lippert, 2007).

Based on the findings of studies that integrated trust into a UTAUT framework (Alam et al., 2020; Chao, 2019; Jang et al., 2016; Papa et al., 2020; Sarkar et al., 2020), trust in technology (Casey & Wilson-Evered, 2012) and trust in brand (intimacy) (Srivastava, Dash, & Mookerjee, 2015), we determined that customers' willingness to use OIPT will be greatly influenced by their confidence in brand and technology, both of which are significant components of trust within the life insurance industry. We looked at previous research that defined trust as an aggregate construct with two distinct components—cognitive and affective—in an attempt to embrace a definition of trust that is well-supported. This study classifies brand reputation as an emotional trust and technology trust as cognitive trust. Given the significance of the notion, our conceptual model of trust in life insurance included elements of both technological trust and brand intimacy, the two types of trust were operationalized as a lower order trust. Using a higher-order structural equation modelling (SEM) results in a more parsimonious model, which in turn performs better on goodness of fit indices (Hair et al., 2010). When a higher-order factor is incorporated into a model, it consumes fewer degrees of freedom, leading to better model fit.

Hypothesis Development

Based on the theoretical relationships described above, the framework can be drawn (Fig.2).

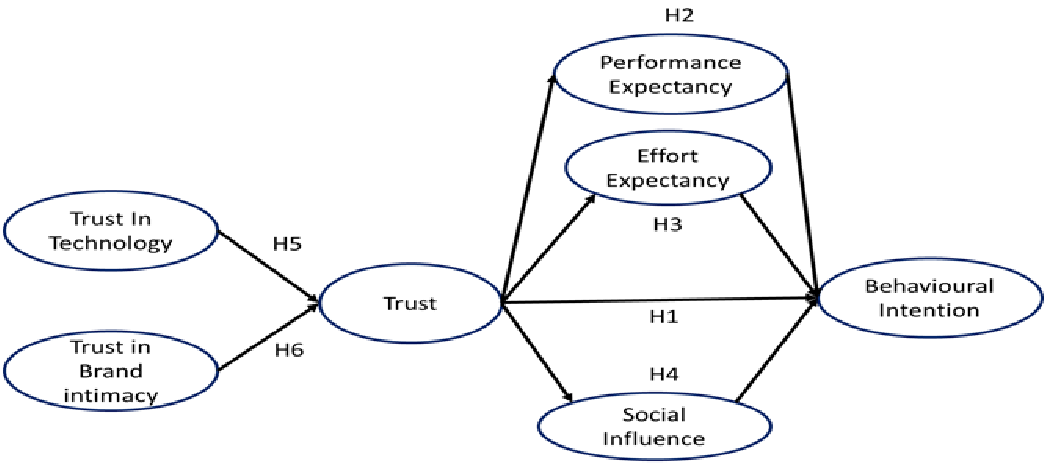

Figure 2. Conceptual framework

Six research hypotheses then be formulated as the following
H1. Trust will have a positive effect on behavioural intention
H2. Performance expectancy mediate the relationship between trust and behavioural intention
H3. Effort expectancy mediate the relationship between trust and behavioural intention
H4. Social influence mediates the relationship between trust and behavioural intention
H5. Trust in Technology will have a positive effect on behavioural intention
H6. Trust in Brand intimacy will have positive effects on behavioural intention.

Methods

Empirical data were collected using a cross-sectional survey using a questionnaire, consisted of items of performance expectancy, effort expectancy, social influence and behavioural intention to use OIPT adopted based on Venkatesh et al. (2003). Items of trust in brand intimacy were adopted based on Srivastava et al. (2015), and items of trust in technology were adopted based on Casey and Wilson-Evered (2012). In this study, trust was conceptualised as a higher order construct (HOC) following a comprehensive analysis of the literature and operationalised as a second-order construct comprising two first-order constructs: trust in technology and trust in brand (intimacy). In this study, a second-order construct can be approximated using commonly-used approach is the repeated indicator approach, also known as the hierarchical component model (Lohmöller & Lohmöller, 1989). A second-order factor is directly measured by using items of all its lower-order factors. The repeated indicator procedure works best when the lower-order constructs have about equal numbers of indicators. In this study we have three equal numbers of indicators in each variable.
The data collected through questionnaire consisted of seventeen items designed on the basis of the theoretical background and measured on a five-point Likert-type scale (1=strongly disagree, 5=strongly agree). Technical terms were consistently explained throughout the study. Purposeful sampling was employed as a technique in Greater Jakarta, based on two criteria: 1) having at least one form of life insurance protection and 2) being 21 years old or older. This

study used 210 samples. To test the model, a partial least squares technique in structural equation modelling (PLS-SEM) was used with SmartPLS3 software in 2021. This method works well for complex models on small samples. It is a method of predicting that does not require a strong theoretical framework (Henseler et al., 2014).

Findings

Respondent Profile

Table 1 shows an almost double number of male than female participants, and 46% of the respondent are in age group >50 years old. Data analysis revealed five age groups consisting of the following: 17-25 years (n=64), 26-35 years (n=33), 36-45 years (n=32), 46-55 years (n=38), and 56 years and above (n=53). The majority of respondents (n=124) had completed only secondary school or lower (n=58), whereas fewer participants had degrees or diplomas (n=29 and n=11 respectively).

Table 1 Respondent Profile

Characteristics	Category	Count	Percentage	Characteristics	Category	Count	Percentage
Gender	Female	76	36%	Level of Income (million)	IDR < 10	55	26%
	Male	134	64%		IDR 10 - 25	57	27%
Age group	21–30	53	25%		IDR 25- 50	50	24%
	31–40	27	13%		IDR > 51	48	23%
	41–50	34	16%	Occupation	Employee	88	42%
	>50	96	46%		Government	40	19%
Education	PhD	7	3%		Entrepreneur	25	12%
	Master	68	32%		Public Figure	4	2%
	Bachelor	112	53%		Agent / Bancassurance	2	1%
	Diploma	5	2%		Others	51	24%
	Highschool	14	7%				
	Others	4	2%				

Source: SPSS Report, 2021

According to Table 1, most participants (n = 57) made between £500 and £1250 a month. 88 (42%) of the 210 respondents worked for private businesses in a variety of industries. The majority of participants—64% of whom were male and over 50—had bachelor's degrees, which was the greatest level of education (53%).

Measurement model

The evaluation of a model (Fig.3) using PLS-SEM is often a two-step procedure that includes evaluations of the measurement model and the structural model (Chin, Henseler, & Wang, 2010; Hair, Ringle, & Sarstedt, 2011). The validation and reliability of the measurement model are evaluated using the model's latent variables. The links between the variables and their related items (replies to individual question-statements in the questionnaire) are assessed in this examination. The structural model's evaluation is focused with the interactions between variables (Chin et al., 2010; Hair et al., 2011).Because this study employed a single source of respondent to gather data on both dependent and independent components, common method variance must be checked (Tehseen, Ramayah, & Sajilan, 2017). To test for common method variance, we assessed the collinearity among constructs. The variance inflation factors are assessed (Kock & Lynn, 2012). These variance inflation factors may be employed to evaluate common method variance, resulting in a more conservative test than the usual exploratory factor analysis (Kock, 2014; Kock & Lynn, 2012). All of the constructs in the model have a complete collinearity variance inflation factor less than 5 (Hair et al., 2014). As a result of testing for common method variance using VIF, we can safely infer that common method bias did not pose a significant risk in the current study (Table 4).

This study's measurement model included four components, one of which (trust) is operationalized as a reflective-formative second order construct. Each of them was evaluated using three items. The measuring model's reliability and validity are assessed. As can be seen in Fig. 3, the model developed as hierarchical component model (HCM), in a reflective-formative structural model. The evaluation of the measurement model is provided in Table 2, which is similar to those in reflective-reflective model. Convergent validity is frequently tested using two essential factors: the composite reliability (CR) and the average variance extracted (AVE) (Chin et al., 2010; Hair et al., 2011). When evaluating a model's convergent validity, the loading of each indicator on its related variable must be computed and compared to a threshold.

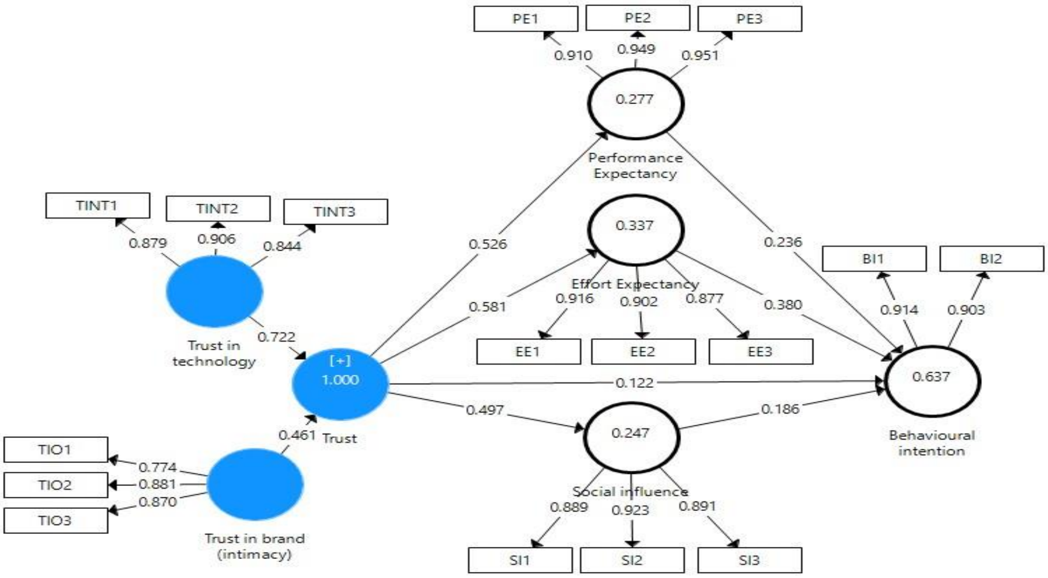

Figure 3. Research Model

In general, the loading should be greater than 0.7 for validity to be deemed satisfactory (Hair et al., 2011). A loading lower than 0.4 indicates that an item should be considered for removal, and items with a loading of 0.4–0.7 should be considered for removal if their removal increases the CRs and AVEs above the threshold (Chin et al., 2010; Hair et al., 2011) .

Table 2 Evaluation results of measurement model.

Construct & Items		Loading	CR	AVE
Performance Expectancy				
PE1	Using (OIPT) would increase the chance of purchase and payment of insurance premium online	0.910	0.930	0.878
PE2	Using OIPT would enhance the current payment process	0.949		
PE3	People would find premium payment portal useful in their jobs	0.951		
Effort Expectancy				
EE1	I would find an OIPT easy to use	0.916	0.926	0.807
EE2	Learning how to operate an OIPT system would be easy for me	0.902		
EE3	The use of an OIPT system would be clear and understandable to me	0.877		
Social Influence				

SI1	In general, insurance agent, bancassurance, and staff has supported the introduction of OIPT	0.889	0.928	0.812
SI2	People who influence my behavior think that using OIPT is a good idea	0.923		
SI3	People who are important to me think that using OIPT is a good idea	0.891		
Trust in Brand Intimacy				
TIO1	I would feel comfortable sharing detailed personal information about myself	0.774	0.880	0.711
TIO2	This brand really understands my need in life insurance product category	0.881		
TIO3	I am familiar with the range of products and services offered by this brand	0.870		
Trust in Technology				
TINT1	I could rely on an OIPT system to be working when I need it	0.879	0.909	0.768
TINT2	An OIPT system would operate in a truthful manner	0.906		
TINT3	An OIPT system would keep its commitments	0.844		

Source: PLS-SEM3 Report 2021

Table 2 indicates that most indicator loadings on their respective variables exceeded 0.7. The CR coefficient gauges construct reliability, which is separate but linked to validity. (Chin et al., 2010). CR is usually considered the more suitable because it incorporates information about the item loadings into its calculation (Hair et al., 2011). The AVEs of the variables should also be more than 0.5 for their convergent validity to be considered acceptable (Chin, 2010; Hair et al., 2011). Table 2 demonstrates that the AVEs of the constructions were more than 0.5. As a result, the measurement model's convergent validity is acceptable. Additionally, we determined that it was unnecessary to remove any of the indicators with loadings between 0.4 and 0.7 because the CR and AVE thresholds had already been reached. The CRs for every variable in the measurement model exceeded 0.8 (Table 2).

Structural Model

Evaluating the structural model consists of assessing for coefficient of determination (R^2), path coefficient (β), collinearity issues (VIF), the effect sizes (f^2) (Hair Jr, Sarstedt, Hopkins, & Kuppelwieser, 2014). The coefficient of determination of R^2 measures the dependent variable's variance about the independent variable's change. The R^2 value ranges from 0 to 1 (Table 3), with a higher score showing higher precision levels. R^2 values of 0.25, 0.5, or 0.75 for an endogenous variable can be portrayed as weak, moderate, or substantial (Hair et al., 2011).

Table 3 Coefficient of Determination (R^2)

	R Square
Behavioral intention	0.638
Effort Expectancy	0.348
Performance Expectancy	0.287
Social influence	0.252
Trust	1

Source: PLS-SEM Report 2023

As can be seen in Table 3 the R^2 of behavioral intention has a high R^2 (0.637) which means that the model explains or predicts 63.7% of the relationship between the dependent and independent variables.

The second criteria on structural model evaluation is a path coefficient, which shows the correlation between two variables, ranging from -1.00 to 1.00. A correlation of 0 shows no relationship at all, a correlation of 1.0 indicates a perfect positive correlation, and a value of -1 shows a perfect negative correlation.

Table 4 Path coefficients

	Path coefficient
Effort Expectancy → Behavioural intention	0.380
Performance Expectancy → Behavioural intention	0.236
Social influence → Behavioural intention	0.186
Trust → Behavioural intention	0.122
Trust → Effort Expectancy	0.581
Trust → Performance Expectancy	0.526
Trust → Social influence	0.497
Trust in brand (intimacy) →Trust	0.461
Trust in technology → Trust	0.722

As shown in Table 4. Effort expectancy has the highest direct effect on behavioral intention (0.380), followed by Performance expectancy (0.236) Social influence (0.186) and Trust (0.122). Trust in technology has a higher strength of relationship on HOC Trust (0.722), than trust in brand (0.461).

The third criterion in structural model evaluation is multicollinearity. The result in Table 5 indicates of no collinearity issues because all of the VIF values are below 5 (Hair Jr et al., 2014).

Table 5 Inner VIF

	Behavioural intention
Effort Expectancy	3.341
Performance Expectancy	2.862
Social influence	1.759
Trust	1.593

The fourth criterion in structural model evaluation is the f^2 values, which assesses a predictor variable on an independent variable (Hair et al., 2014). which ranging from .02, .15, and .35, correspondingly, indicate small, medium, and large effect sizes (Cohen, 1988).

Table 6. f^2 values

	Behavioural intention	Effort Expectancy	Performance Expectancy	Social influence
Effort Expectancy	0.119			
Performance Expectancy	0.053			
Social influence	0.054			
Trust	0.026	0.509	0.383	0.329

Table 6 shown, the model has a large effect of Trust on Effort expectancy (.509), followed by Trust on Performance expectancy (0.383), and Trust on Social influence (0.329).

The last step in data analysis used SmartPLS3 is to test the hypothesized relationships by assessing the path coefficients' significance using bootstrapping computations. The hypothesis was tested using the bootstrapping test that obtains the significance of path coefficients by calculating empirical t values, which are larger than the critical value (t distribution values). The coefficient is considered significant at a particular probability of error. recommend that the bootstrap samples are 5000. Hypotheses testing was carried out using the bootstrapping technique in SmartPLS3 to assess path coefficients' significance. Using one tails t-value is

1.65, at significance level α = 5%), the p value should smaller than 0.05 in order to render the relationship under consideration significant (Hair et al., 2014).

Table 7 Evaluation results of structural model

	Hypothesis	β	p value	Supported
H1	Trust → Behavioral intention to adopt OIPT	0.122	0.025	Yes
H2	Trust → Performance Expectancy → Behavioural intention	0.124	0.010	Yes
H3	Trust → Effort Expectancy → Behavioural intention	0.221	0.000	Yes
H4	Trust → Social Influence → Behavioural intention	0.092	0.003	Yes
H5	Trust in technology → Trust → Behavioral intention	0.088	0.027	Yes
H6	Trust in brand (intimacy) → Trust → Behavioral intention	0.056	0.024	Yes

As can be seen in Table 7, all p-values are smaller than 0.05 (at α = 5%). According to Joseph F Hair Jr et al. (2016), all effects are significant; therefore, H1to H4 is supported. The β coefficient showing the strength of the indirect effect between Trust and Behavioral Intention mediated by Effort Expectancy has the highest value (0.221) compare to Performance Expectancy (0.124), and Social Influence (0.092). In a reflective-formative model, we can also evaluate the specific indirect effect on Behavioral Intention (Table 8).
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Table 8 Specific Indirect Effect of LOC Trust on Behavioral Intention

	Indirect effect	p-value
Trust in technology → Effort Expectancy → Behavioral intention	0.159	0.000
Trust in brand (intimacy) →Effort Expectancy→ Behavioral intention	0.102	0.000
Trust in technology → Performance Expectancy → Behavioral intention	0.090	0.012
Trust in technology → Behavioral intention	0.088	0.027
Trust in technology → Social influence → Behavioral intention	0.067	0.003
Trust in brand (intimacy) → Performance Expectancy → Behavioral intention	0.057	0.011
Trust in brand (intimacy) → Behavioral intention	0.056	0.024
Trust in brand (intimacy) → Social influence → Behavioral intention	0.043	0.002

Table 8 shown a specific indirect effect of two different Trust towards behavioural intention through different path. As can be seen, the path with the greatest indirect effect influence on behavioural intention is Trust in technology → Effort Expectancy → Behavioural intention (.159) followed by Trust in brand → Effort Expectancy → Behavioural intention (.102). The path with the lowest influence is Trust in brand intimacy → Social influence → Behavioural intention (.043)

Discussion and Conclusion

The primary objective of this study is the assessment of the effectiveness of HOC Trust as a predictor of an individual's intention to use OIPT. We began with the evaluation of the core UTAUT model by evaluating Performance Expectancy, Effort Expectancy, Social Influence and their influence on Behavioral intention. Performance expectancy (PE), as indicated by the literature review conducted, is usually the most relevant variable for explaining the adoption of new technologies. Our results show that and consistent with the study Jiang et al. (2019) in life insurance industry. The obtained results show that the variable with the greatest influence on behavioral intention is effort expectancy (EE) has a significant and positive impact on behavioral intention, which is consistent with the literature. Social influence (SI) has a positive and significant effect on behavioral intention. This result is consistent with the studies reviewed in the context of life insurance (Mazuri et al., 2017). We have verified that trust also has a significant and positive impact on behavioral intention. This was the expected result given the confluence of the intrinsic nature of the insurance business, which is based on trust (de Andrés-Sánchez et al., 2021). Unlike other study by (de Andrés-Sánchez et al., 2021) in Spain which obtained that Social Influence is the variable with the highest influence, our result revealed that Social influence is the weakest relationship in the model (0.186), however the effect is significant, indicate by the p-value less than 0.05. The finding is consistent with previous findings Venkatesh et al. (2003), the results of this study support the inclusion of social influence as a predictor of behavioural intention. The study was carried out during the pandemic period of COVID-19. It is expected that the strength of relationships between UTAUT constructs in the model may change after exposure to actual OIPT technology.

We have verified that trust also has a significant and positive impact on behavioral intention. The study ascertained that Trust has a direct effect on behavioral intention, but the correlation is feeble, particularly in the extended model of UTAUT in the framework of insurance online purchasing and payment technology (OIPT). This was the expected result given the confluence of the intrinsic nature of the insurance business, which is based on trust (de Andrés-Sánchez et al., 2021) This result is consistent with the studies reviewed in the context of life insurance (de Andrés-Sánchez et al., 2021). and the relevance of this construct in the acceptance of online insurance payment technology, which make this factor highly relevant in life insurance industry. Our results coincide with (Huang, Chang, & Sia, 2019) in the acceptance of new techs in insurance settings. This study highlights the usefulness of conducting research on technology acceptance and supports the use of an expanded version of the UTAUT framework that includes trust in technology.

In general, the research model explicated over 63.8% of the variance in Behavioral intention. Another noteworthy discovery is that the R2 value of Effort Expectancy exceeds that of Performance Expectancy and Social Influence. This outcome suggests that Effort Expectancy holds greater sway over behavioral intention to utilize OIPT. The key determinants of Behavioral intention were Effort expectancy, Performance Expectancy, Social influence, and Trust, all of which had a direct impact on the intention to use OIPT. These findings are in line with those of a previous study. (Chao, 2019; Jiang et al., 2019; Mazuri et al., 2017; Panigrahi et al., 2018).

The second objective of the study is to investigate the role of performance expectation, effort expectancy, and social influence as a mediator between trust and behavioural intention to use OIPT. The study provides some support for our hypothesis, that each of UTAUT predictors namely performance expectancy, effort expectancy and social influence expectancy has mediating role in the relationship between HOC Trust and behaviour intention to use OIPT. Effort expectancy has the strongest mediating effect, and social influence has a weakest mediating effect. The direct effect of HOC Trust slightly lower than the indirect effect using Effort expectancy, suggest that to improve behavioural intention to use OIPT, the information strategy management in insurance company, the Effort expectancy variable should be taken care more, because it gives a stronger indirect effect. However total effect of HOC Trust on Behavioural intention gives the largest effect compare to total effect of Effort expectancy on Behavioural intention. This finding is consistent with previous studies (Casey & Wilson-Evered, 2012).

The third objective of this study is to examine the weights of two LOC Trust in technology and Trust in brand intimacy. The result in Figure 2 indicate that Trust in technology has a stronger effect on HOC Trust (0.722), compare to Trust in brand intimacy (0.461). The result can be interpreted as the heaviest component of HOC Trust in life insurance industry is a cognitive Trust, measured by ability, professionalism and reliability.

Theoretical Implications

We utilized UTAUT and incorporated HOC Trust into the model and examined the direct and indirect effect of HOC Trust on Behavioural intention. In this study Performance expectancy, Effort Expectancy and Social influence were tested as a moderator. In addition, most previous studies incorporating emotional Trust into behavioural intention have been undertaken in many industries, and this study conducted in life insurance industry in developing country. The use of HOC Trust in UTAUT model and in industry context considered among the first in the Behavioural intention theory using UTAUT, and need further test in different context

Practical and Social Implications

The model's application demonstrates trust's crucial role in technology adoption within the insurance industry. The practical implications of this study's results are significant for information strategy management in companies. Our findings indicate that effort expectancy strongly influences the behavioural intention to utilise OIPT. Therefore, the management should strive to enhance the accessibility and usability of the website, in order to elicit positive attitudes towards the use of online insurance payment technology by customers. Engaging customers in the creation of websites and conducting periodic A/B testing can significantly augment the perceived ease of use of the website. It is imperative that these efforts target the younger generation, who are more technologically proficient, health-conscious, and capable of paying insurance premiums.

Limitations and Suggestions for Future Research

We are aware of the limitations of the empirical work presented. This study was conducted in a specific are, Great Jakarta in Indonesia, using purposive sampling based on two criteria: 1) having at least one form of life insurance protection and 2) being 21 years old or older. Most responses were obtained from male (64%) and age above 50 years old (46%). Among of them (20%) are government employee. Thus, generation, gender and culture may bias our conclusions about the behavioural intention to use online payment in website. Therefore, it is advisable to exercise caution when extrapolating our findings to policyholders/insureds from private companies, or could obtained more respondents from, millennials generation, and career women, since these age groups have been known to display different behaviour and career woman may give different perspective about emotional trust.

References

Alalwan, A. A., Dwivedi, Y. K., & Rana, N. P. (2017). Factors influencing adoption of mobile banking by Jordanian bank customers: Extending UTAUT2 with trust. *International Journal of Information Management, 37*(3), 99-110.

Alalwan, A. A., Dwivedi, Y. K., Rana, N. P., & Algharabat, R. (2018). Examining factors influencing Jordanian customers’ intentions and adoption of internet banking: Extending UTAUT2 with risk. *Journal of Retailing and Consumer Services, 40*, 125-138.

Alam, M. Z., Hu, W., Kaium, M. A., Hoque, M. R., & Alam, M. M. D. (2020). Understanding the determinants of mHealth apps adoption in Bangladesh: A SEM-Neural network approach. *Technology in Society, 61*, 101255.

Alharbi, S. T. (2014). *Trust and acceptance of cloud computing: A revised UTAUT model.* Paper presented at the 2014 international conference on computational science and computational intelligence.

Amoako-Gyampah, K., & Salam, A. F. (2004). An extension of the technology acceptance model in an ERP implementation environment. *Information & Management*, *41*(6), 731-745.

Arfi, W. B., Nasr, I. B., Kondrateva, G., & Hikkerova, L. (2021). The role of trust in intention to use the IoT in eHealth: Application of the modified UTAUT in a consumer context. *Technological Forecasting and Social Change, 167*, 120688.

Casey, T., & Wilson-Evered, E. (2012). Predicting uptake of technology innovations in online family dispute resolution services: An application and extension of the UTAUT. *Computers in human behavior, 28*(6), 2034-2045.

Chao, C.-M. (2019). Factors determining the behavioral intention to use mobile learning: An application and extension of the UTAUT model. *Frontiers in psychology, 10*, 1652.

Chauhan, S., & Jaiswal, M. (2016). Determinants of acceptance of ERP software training in business schools: Empirical investigation using UTAUT model. *The International Journal of Management Education, 14*(3), 248-262.

Chen, S. J., Waseem, D., Xia, Z. R., Tran, K. T., Li, Y., & Yao, J. (2021). To disclose or to falsify: The effects of cognitive trust and affective trust on customer cooperation in contact tracing. *International Journal of Hospitality Management, 94*, 102867.

Chin, W. W., Henseler, J., & Wang, H. (2010). *Handbook of partial least squares* (Vol. 201): Springer.

Cimperman, M., Brenčič, M. M., & Trkman, P. (2016). Analyzing older users' home telehealth services acceptance behavior—applying an Extended UTAUT model. *International journal of medical informatics, 90*, 22-31.

Cohen, J. (1988). Statistical power analysis for the behavioral sciences–second edition. 12 Lawrence Erlbaum Associates Inc. *Hillsdale, New Jersey, 13*.

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

de Andrés-Sánchez, J., González-Vila Puchades, L., & Arias-Oliva, M. (2021). Factors influencing policyholders' acceptance of life settlements: a technology acceptance model. *The Geneva papers on risk and insurance-issues and practice*, 1-27.

Duyck, P., Pynoo, B., Devolder, P., Voet, T., Adang, L., & Vercruysse, J. (2008). User acceptance of a picture archiving and communication system. *Methods of information in medicine, 47*(02), 149-156.

Gupta, B., Dasgupta, S., & Gupta, A. (2008). Adoption of ICT in a government organization in a developing country: An empirical study. *The Journal of Strategic Information Systems, 17*(2), 140-154.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing theory and Practice, 19*(2), 139-152.

Hair Jr, J. F., Sarstedt, M., Hopkins, L., & Kuppelwieser, V. G. (2014). Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research. *European business review, 26*(2), 106-121.

Helmi, A. (2014). Consumers' trust as the mediating factor for insurance buying intention In Indonesia. *Statistics, 3,* 894.

Hoff, K. A., & Bashir, M. (2015). Trust in automation: Integrating empirical evidence on factors that influence trust. *Human factors, 57*(3), 407-434.

Hoque, R., & Sorwar, G. (2017). Understanding factors influencing the adoption of mHealth by the elderly: An extension of the UTAUT model. *International journal of medical informatics, 101*, 75-84.

Huang, W.-S., Chang, C.-T., & Sia, W. Y. (2019). An empirical study on the consumers' willingness to insure online. *Polish Journal of Management Studies, 20*.

Jang, S. H., Kim, R. H., & Lee, C. W. (2016). Effect of u-healthcare service quality on usage intention in a healthcare service. *Technological Forecasting and Social Change, 113*, 396-403.

Jiang, S.-j., Liu, X., Liu, N., & Xiang, F. (2019). Online life insurance purchasing intention: Applying the unified theory of acceptance and use of technology. *Social Behavior and Personality: an international journal, 47*(7), 1-13.

Kabra, G., Ramesh, A., Akhtar, P., & Dash, M. K. (2017). Understanding behavioural intention to use information technology: Insights from humanitarian practitioners. *Telematics and Informatics, 34*(7), 1250-1261.

Khalilzadeh, J., Ozturk, A. B., & Bilgihan, A. (2017). Security-related factors in extended UTAUT model for NFC based mobile payment in the restaurant industry. *Computers in human behavior, 70*, 460-474.

Kock, N. (2014). Advanced mediating effects tests, multi-group analyses, and measurement model assessments in PLS-based SEM. *International Journal of e-Collaboration (ijec), 10*(1), 1-13.

Kock, N., & Lynn, G. (2012). Lateral collinearity and misleading results in variance-based SEM: An illustration and recommendations. *Journal of the Association for information Systems, 13*(7).

Lim, S. H., Hur, Y., Lee, S., & Koh, C. E. (2009). Role of trust in adoption of online auto insurance. *Journal of Computer Information Systems, 50*(2), 151-159.

Lippert, S. K. (2007). Investigating postadoption utilization: An examination into the role of interorganizational and technology trust. *IEEE Transactions on Engineering Management, 54*(3), 468-483.

Lippert, S. K., & Ojumu, E. B. (2008). Thinking outside of the ballot box: Examining public trust in e-voting technology. *Journal of Organizational and End User Computing (JOEUC), 20*(3), 57-80.

Lohmöller, J.-B., & Lohmöller, J.-B. (1989). Predictive vs. structural modeling: Pls vs. ml. *Latent variable path modeling with partial least squares*, 199-226.

Luo, J. S., Hilty, D. M., Worley, L. L., & Yager, J. (2006). Considerations in change management related to technology. *Academic Psychiatry, 30*, 465-469.

Luo, X., Li, H., Zhang, J., & Shim, J. P. (2010). Examining multi-dimensional trust and multi-faceted risk in initial acceptance of emerging technologies: An empirical study of mobile banking services. *Decision support systems, 49*(2), 222-234.

Maillet, É., Mathieu, L., & Sicotte, C. (2015). Modeling factors explaining the acceptance, actual use and satisfaction of nurses using an Electronic Patient Record in acute care settings: An extension of the UTAUT. *International journal of medical informatics, 84*(1), 36-47.

Martins, C., Oliveira, T., & Popovič, A. (2014). Understanding the Internet banking adoption: A unified theory of acceptance and use of technology and perceived risk application. *International Journal of Information Management, 34*(1), 1-13.

Mazuri, A. G., Samar, R., & Fatin Jamilah, M. (2017). Inspecting the role of intention to trust and online purchase in developing countries. *Journal of Socialomics, 6*(1), 1-7.

McAllister, D. J. (1995). Affect-and cognition-based trust as foundations for interpersonal cooperation in organizations. *Academy of management journal, 38*(1), 24-59.

McKnight, D. H., & Chervany, N. L. (2001). What trust means in e-commerce customer relationships: An interdisciplinary conceptual typology. *International Journal of Electronic Commerce, 6*(2), 35-59.

Naidu, C., & Paramasivan, C. (2015). Emergence and growth of online life insurance in India. *International Journal of Management and Social Science Research Review, 1*, 38-40.

Nov, O., & Ye, C. (2009). Resistance to change and the adoption of digital libraries: An integrative model. *Journal of the American Society for Information Science and Technology, 60*(8), 1702-1708.

Panigrahi, S., Azizan, N. A., & Waris, M. (2018). Investigating the empirical relationship between service quality, trust, satisfaction, and intention of customers purchasing life insurance products. *Indian Journal of Marketing• January*.

Papa, A., Mital, M., Pisano, P., & Del Giudice, M. (2020). E-health and wellbeing monitoring using smart healthcare devices: An empirical investigation. *Technological Forecasting and Social Change, 153*, 119226.

Pinquet, J., Guillén, M., & Ayuso, M. (2011). Commitment and lapse behavior in long-term insurance: a case study. *Journal of Risk and Insurance, 78*(4), 983-1002.

Sánchez-Prieto, J. C., Olmos-Migueláñez, S., & García-Peñalvo, F. J. (2016). Informal tools in formal contexts: Development of a model to assess the acceptance of mobile technologies among teachers. *Computers in human behavior, 55*, 519-528.

Sarkar, S., Chauhan, S., & Khare, A. (2020). A meta-analysis of antecedents and consequences of trust in mobile commerce. *International Journal of Information Management, 50*, 286-301.

Srivastava, N., Dash, S. B., & Mookerjee, A. (2015). Antecedents and moderators of brand trust in the context of baby care toiletries. *Journal of Consumer Marketing, 32*(5), 328-340.

Straub, E. T. (2009). Understanding technology adoption: Theory and future directions for informal learning. *Review of educational research, 79*(2), 625-649.

Su, N., & Mattila, A. S. (2020). Does gender bias exist? The impact of gender congruity on consumer's Airbnb booking intention and the mediating role of trust. *International Journal of Hospitality Management, 89*, 102405.

Šumak, B., Pušnik, M., Heričko, M., & Šorgo, A. (2017). Differences between prospective, existing, and former users of interactive whiteboards on external factors affecting their adoption, usage and abandonment. *Computers in human behavior, 72*, 733-756.

Šumak, B., & Šorgo, A. (2016). The acceptance and use of interactive whiteboards among teachers: Differences in UTAUT determinants between pre-and post-adopters. *Computers in human behavior, 64*, 602-620.

Tehseen, S., Ramayah, T., & Sajilan, S. (2017). Testing and controlling for common method variance: A review of available methods. *Journal of management sciences, 4*(2), 142-168.

Tsai, Y.-Y., Chao, C.-M., Lin, H.-M., & Cheng, B.-W. (2018). Nursing staff intentions to continuously use a blended e-learning system from an integrative perspective. *Quality & Quantity, 52*, 2495-2513.

Van Raaij, E. M., & Schepers, J. J. (2008). The acceptance and use of a virtual learning environment in China. *Computers & education, 50*(3), 838-852.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly*, 425-478.

Zhao, Y., Zhao, Y., Yuan, X., & Zhou, R. (2018). How knowledge contributor characteristics and reputation affect user payment decision in paid Q&A? An empirical analysis from the perspective of trust theory. *Electronic Commerce Research and Applications, 31*, 1-11.