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Performance and Effort Expectancy as Antecedents of Mobile Life Insurance Purchase Intention in Zimbabwe

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Abstract:

The COVID-19 pandemic severely crippled the traditional face-to-face life insurance distribution model which dominated the global life insurance market for centuries. Digital distribution channels that life insurers have long ignored now present the only viable alternative. This article assessed consumers' perceptions of the use of mobile technology in purchasing life insurance in Zimbabwe. It was underpinned by The Unified Theory of Acceptance and Use of Technology (UTAUT) model's performance expectancy and effort expectancy constructs. The survey collected data from 250 randomly selected customers of a large Zimbabwean life assurance firm using an online, five-point Likert scale questionnaire. Hierarchical multiple linear regression modelling was adopted to evaluate the effects of performance expectancy (PE) and effort expectancy (EE) on mobile insurance purchase intentions (PI), after controlling for the effects of age and education. The results revealed that customers' mobile life insurance purchase intentions were significantly influenced by performance expectancy ($p<0.01$) and effort expectancy ($p<0.01$). The study concluded that young and educated consumers were more likely to use mobile gadgets to purchase life insurance if they perceived that the mobile sales platform is effective, productive, and useful, and the process requires little effort. These findings offer Zimbabwean life insurers guidelines for product design, development, and marketing through mobile channels considering the COVID-19 pandemic.

Keywords:

Performance Expectancy, Effort Expectancy, Purchase Intention, Traditional Insurer, Mobile Life Insurance.

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Introduction

The life insurance sector has long relied on face-to-face interactions for policy distribution, facilitated by intermediaries such as agents, brokers, and financial advisors. This traditional model has dominated the global life insurance market for decades (Singh et al., 2020; Insurance Information, 2021). However, the outbreak of the COVID-19 pandemic severely disrupted conventional distribution channels, prompting insurers to explore digital alternatives (Swiss Re, 2020). Due to restrictions on face-to-face engagement, mobile technology has emerged as a promising platform for life insurance transactions. Mobile distribution is particularly relevant in contexts where digital literacy is high and mobile device penetration is significant, such as Zimbabwe.

Despite the clear potential of mobile platforms, their adoption within the life insurance sector remains limited, especially in developing economies. Mobile insurance adoption has been slower than that observed in other financial services like mobile banking, where digital transformation has progressed more rapidly (Moodley, 2019; OECD, 2020). While several studies have investigated mobile technology adoption using models such as the Technology Acceptance Model (TAM) (Davis et al., 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), few have specifically examined mobile life insurance adoption in Zimbabwe. Previous research has highlighted key factors influencing technology uptake, such as performance expectancy and effort expectancy, yet these determinants have mainly been explored in mobile banking or e-commerce contexts (Wu and Wang, 2005; Pikkarainen et al., 2004). As a result, a knowledge gap persists regarding the application of these constructs in mobile life insurance within developing markets like Zimbabwe.

Understanding mobile life insurance adoption is significant for both academic and practical reasons. From an academic perspective, this study addresses the gap in literature concerning the application of the UTAUT model to mobile insurance adoption in Zimbabwe. Previous studies have focused predominantly on Western contexts or non-insurance sectors, making it crucial to explore this topic within a different socio-economic environment (El Arif, 2020; Prykaziuk et al., 2021). Practically, the study offers insights into how life insurers can enhance mobile adoption rates by focusing on performance and effort expectancy. Given that mobile distribution channels reduce costs and foster closer customer engagement (OECD, 2020), it is essential for insurers to understand consumer perceptions of mobile technology. The findings of this research are particularly timely, as the COVID-19 pandemic has accelerated the shift towards digital insurance solutions (Pauch & Bera, 2022; Yadav & Suryavanshi, 2021).

This paper aims to investigate how performance expectancy and effort expectancy influence mobile life insurance purchase intentions among Zimbabwean consumers. By applying the UTAUT framework, the study seeks to provide empirical evidence on the role of these constructs in shaping consumer behaviour. Additionally, the research intends to offer practical guidance for insurers seeking to optimise mobile platforms to attract and retain customers. Understanding the factors that motivate or hinder mobile insurance adoption will aid insurers in developing targeted strategies to increase usage, especially amid challenges posed by the pandemic.

The primary research question guiding this study is:

- How do performance expectancy and effort expectancy influence mobile life insurance purchase intentions among consumers in Zimbabwe?

To gain a comprehensive understanding, the following sub-questions will also be addressed.

- What is the relationship between performance expectancy and the intention to purchase mobile life insurance?
- How does effort expectancy affect mobile life insurance purchase intentions among consumers?
- How do demographic factors such as age and education moderate the relationships between these constructs and purchase intentions?

Literature Review

The Life Insurance Distribution Channel

Insurance distribution refers to the method by which a firm provides its products and services or, more broadly, how insurers interact with clients (Bravo, 2021). It plays a central role in the business model and extends beyond sales activities (Bravo, 2021). It includes information exchange, price communication, negotiation, transaction completion, and post-sale engagement (Pain et al., 2014). Insurance markets often exhibit asymmetric and incomplete information (Zweifel et al., 2021). Customers may lack awareness of product options, while insurers may not fully understand customer risk profiles (Boodhun & Jayabalan, 2018; Dosis, 2018). Intermediaries help address these gaps by reducing costs and improving coordination (Dominique-Ferreira, 2018). Historically, life insurance in the United Kingdom, Australia, and the United States was distributed by tied agents (Goh, 2012). The model later expanded to include brokers and internal staff (Pain et al., 2014). Today, distribution also involves e-commerce, telesales, bancassurance, and corporate partners (Pain et al., 2014).

Future of Insurance Distribution

Technological development and innovation are expected to transform business processes, with automation potentially affecting 30 percent of activities in 60 percent of occupations (Manyika et al., 2017). Numerous authors (e.g., Kappal & Doifode, 2023; Kumaraguru, 2018; OECD, 2020; Suprun et

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al., 2023) predict significant growth in digital insurance distribution, driven by Big Data, Artificial Intelligence, and mobile technology. New non-life insurance start-ups such as PolicyGenius and Lemonade distribute products digitally with AI support (OECD, 2020). The sales process is increasingly expected to be customer-led, made possible by innovations including remote desktop access, digital signatures, video conferencing, and straight through processing (Revathi, 2020).

Mobile Sales Platform: Benefits, Risks, and Limitations

SMS Channel

A life insurance mobile sales platform may employ the short message service technology strategy. SMS is a communication protocol that sends short text messages via mobile devices operating on the Global System for Mobile Communication (Jibril et al., 2014). This channel allows marketers to engage directly with customers through personalised interactions (Shareef et al., 2016). It is particularly effective for delivering time-specific and location-specific product offers, facilitating targeted communication (Shareef et al., 2017). Sellers can take advantage of focused marketing opportunities (Narang & Shankar, 2019) and personalised marketing through SMS is widely recommended (Rowles, 2017). Chow et al. (2022) indicate that over 98 percent of SMS messages are opened compared to only 22 percent of e-mail marketing messages. Zarichna (2021) notes that SMS remains reliable in areas with weak network coverage, as messages can be stored on servers and retrieved when a signal becomes available.

However, the SMS channel has limitations. Message size is restricted to 160 bytes, which may hinder the transmission of complex content (Shareef et al., 2016). While some consider this adequate (Trosby et al., 2010), others view it as limiting (Shareef et al., 2016). The absence of images or visual features reduces its impact (Gavilan et al., 2015). The lack of social interaction prevents validation from opinion leaders or reference groups (Dholakia et al., 2010). Furthermore, consumer scepticism may increase when unfamiliar brands use SMS marketing (Chou & Lien, 2014). Mobile operators may store SMS data and share it with advertisers, leading to unsolicited messages (Van Der Merwe & Van Staden, 2015). An overload of messages can reduce attention to individual content (Weber & Zheng, 2007).

Theoretical Framework

This study is based on two established models of technology adoption: the Technology Acceptance Model (TAM) developed by Davis et al. (1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) introduced by Venkatesh et al. (2003). TAM aims to predict consumer acceptance of technology by examining intention. It explains intention through variables such as perceived usefulness, subjective norms, attitudes, and perceived ease of use (Davis et al., 1989). Perceived usefulness is defined as the belief that using a particular technology will enhance performance, while perceived ease of use relates to expectations regarding its simplicity (Davis et al., 1989). Both models suggest that mobile consumers are more likely to respond positively to a marketer's approach if they perceive the task as useful and easy to complete.

Chuttur (2009) questions the effectiveness of TAM, suggesting that it lacks adequate explanatory and predictive power. The model is considered to oversimplify technology adoption and lacks practical relevance. Studies in mobile commerce and online banking indicate that perceived ease of use may not significantly influence attitudes or intentions (Al-Jabri, 2015; Riptiono et al., 2021). Radić et al. (2024) observe that TAM does not account for cost or external factors affecting adoption. Critics such as Malatji et al. (2020) and Saleh et al. (2020) argue that it overemphasises perceived usefulness, overlooking factors that make technology valuable. Mogaji et al. (2024) attributes TAM's limitations to the rapid advancement of technology.

Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT) was developed by Venkatesh et al. (2003) through an empirical study that combined several earlier models. These included the Technology Acceptance Model, the Theory of Reasoned Action, and the Theory of Planned Behaviour. The UTAUT also incorporates the motivational model, the personal computer use model, social cognitive theory, and innovation diffusion theory (Mohamed et al., 2021). The model suggests that both intentional and actual usage behaviour are influenced by four primary determinants and four moderators (Aytekin et al., 2022). Effort expectancy and performance expectancy influence the intention to use technology, while facilitating conditions affect actual usage (Mohamed et al., 2021). Gender, age, experience, and volition serve as moderators within these relationships (Aytekin et al., 2022). Earlier models explained between 17 and 53 percent of the variance in technology usage intentions, whereas the UTAUT model accounts for between 69 and 70 percent (Venkatesh et al., 2016).

The UTAUT has been extensively validated and is regarded as a robust framework for studying technology adoption (Jiang et al., 2019; Zhou et al., 2019). It has been applied in various contexts, including online and mobile banking (Handayani, 2023; Sarfaraz, 2017; Varma, 2018). In life insurance, Méndez-Aparicio et al. (2017) examined customer expectations for online services, while Jiang et al. (2019) investigated intentions to purchase insurance through online platforms.

Conceptual Framework

This study incorporated constructs from the TAM and the UTAUT models, that have been used by other researchers who have investigated consumer life insurance purchase intentions (Méndez-Aparicio et al., 2017; Jiang et al., 2019). The adopted model's constructs and their controlling demographic variables were defined and discussed within the context of the study. The proposed model is depicted in Figure 1.

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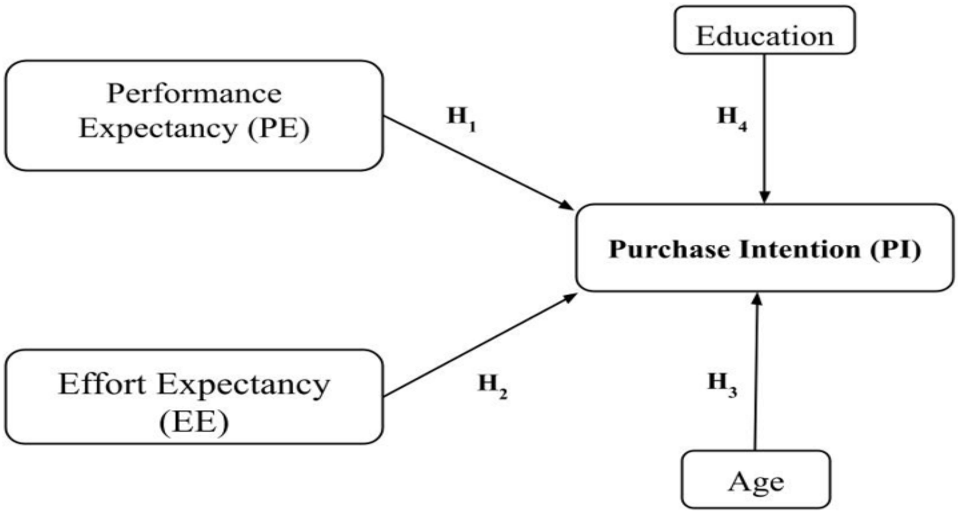

Figure 1: Proposed Model (Source: Adapted from Jiang et al. (2019))

Performance Expectancy

Performance expectancy (PE) refers to consumers' expectations regarding how the use of technology will enhance their ability to perform a specific task (Venkatesh et al., 2016). A key element of this construct is perceived usefulness, which assesses how helpful consumers believe a system, such as mobile technology, is in completing a task (Venkatesh et al., 2016). PE also reflects the perceived advantage of using the mobile insurance channel (Sarfaraz, 2017). It significantly influences customers' intentions to purchase life insurance online (Jiang et al., 2019). Méndez-Aparicio et al. (2017) found that consumers are more likely to buy insurance online if they consider the channel effective and productive. Perceived usefulness also influences insurance managers' adoption decisions (Naicker & Van Der Merwe, 2018). As a result, the research hypothesis (H1) was as follows:

H1: Performance expectancy (PE) has a significant positive influence on consumers' purchase intention of mobile life insurance.

Effort Expectancy

Effort expectancy (EE) is the level of comfort a customer experiences when using technology (Venkatesh et al. 2016). One of the primary motivations for technology adoption has been identified as the requirement for less effort and ease of use (Sarfaraz, 2017). Consumers are more likely to buy if they perceive the online insurance purchasing process to be straightforward and low-effort (Méndez-Aparicio et al., 2017). Jiang et al. (2019) discovered that EE's influence on the intention to purchase online life insurance was significant. These results agree with research on banking technology adoption (Rahi & Ghani, 2019; Sarfaraz, 2017). As a result, our hypothesis (H2) is as follows:

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H2: Effort expectancy has a significant positive influence on consumers' purchase intention of mobile life insurance.

Purchase Intention

Investigators have long used purchase intentions to help predict future purchasing behaviour (Roudposhti et al., 2018). The desire of a consumer to purchase goods or services is referred to as purchase intention (Arifani & Haryanto, 2018). Purchase intention is measured by four indicators: preparing to buy, having a budgeted amount to buy, thinking about buying, and having a strong desire to buy (Diallo, 2012). In our case, the consumers intend to purchase life insurance products using their mobile devices in the future.

Control Variables

Control variables are observable variables that must be held constant to study the impact of independent variables on the dependent variable (Roediger & Yamashiro, 2020). In this study, age and education were incorporated in the research model as control variables. Although they were not the main variables of interest, they could explain the variation in life insurance purchase intentions (Jiang et al., 2019).

Age

Age has been identified as a significant factor in the adoption of new technology (Venkatesh et al., 2016). Chuang et al. (2009) found that individuals aged between 20 and 30 adopt technology more readily than those aged 31 and above. Rony (2019) and Dougherty and Clarke (2018) reported that Generation Y individuals are generally tech-savvy and open to innovation. Boonsiritomachai and Pitchayadejanant (2017) observed that users aged 25 to 40 are active mobile information seekers and more capable of adapting to new technology. This study therefore proposes that younger users are more likely to purchase life insurance via mobile platforms. Therefore, the research hypothesises:

H3: Purchase intentions for the young are significantly higher than for the old.

Level of Education

Consumers with a higher level of education are generally more inclined to use online banking than those with lower educational attainment (Ameme, 2015). Eze et al. (2011) note that executives with advanced formal education are more likely to adopt information technology and promote its benefits across an organisation. However, Jiang et al. (2019) argue that educational background does not influence consumers' willingness to purchase life insurance online. Similarly, Abayomi et al. (2019) and Munusamy et al. (2013) found no link between education and the use of mobile or internet banking. Given Zimbabwe's high literacy rate, this study proposes the following hypothesis.

H4: Purchase intentions for those holding a bachelor's degrees and above are significantly higher than for those with lower qualifications.

Methods and Data

Sampling

A quantitative design and a survey-based method was used to gather and analyse data. The design was chosen because the variables were measured numerically, allowing for the use of known statistical techniques. A large life assurance company was conveniently selected for inclusion in this study. The firm has advanced technologies and enjoys a significant market share of the Zimbabwean life assurance sector. The researchers were convinced that since the COVID-19 pandemic outbreak, the company had already instituted plans to reach out to customers through online platforms. The population was all customers who received services from the firm between January and May 2020. Simple random sampling method was used for participant selection.

Data Collection and Analysis

Data were gathered using an online questionnaire (see for example, Mansour et al., 2014; Nazir & Tian, 2022; Yin et al., 2016). A five-point Likert item questionnaire ranging from strongly disagree (1) to strongly agree (5) was created and coded in Google Forms. A link was generated and sent to the firm for onward distribution to participants through Email and WhatsApp. The data were gathered during the COVID-19 pandemic induced lockdowns, so direct contact with the participants was avoided. Upon completion of the survey by the participant, the responses were collected and stored in Google Sheets ready for cleaning and preliminary analysis. Google forms was chosen because it has a user-friendly graphical user interface, allowing deployment through a web browser on a computer, tablet, or mobile phone. Thus, making the survey easy to complete across devices with different capacities and operating systems. During the data cleaning and validation stage, 34 invalid responses were removed. The final sample consisted of 250 valid responses (88% response rate).

After controlling for the effects of age and education, hierarchical multiple linear regression analysis (HMLRA) in IMBM SPSS v26 was used to evaluate the effects of PE and EE on PI. HMLRA was the preferred approach because it allows one to enter the variables in blocks. Block 1 was made up of the control variable Age. Block 2 was made up of control variables Age and Education, while PE and EE were added in Block 3 during the modelling process. Based on the theoretical model suggested by Doan (2020), the following equation was deduced to suite the current study:

$$PI = b_0 + b_1 Age + b_2 Edu + b_3 PE + b_4 EE \quad \ldots\ldots \text{(1)}$$

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Where PI is the customer's intention to purchase life insurance through a mobile phone. PE is the performance expectancy, EE is the effort expectancy, Age is a control variable dummy coded as 1 if the customer is between 18 and 35 and 0 if the customer is above 35 years. Edu is the customer's level of education, dummy coded as 1 if the customer holds at least a bachelor's degree and 0 for lower-level qualifications.

Variables and Measures

Based on previous research on online insurance purchase intentions, the constructs were operationalized. Measures of performance expectancy (PE), Effort Expectancy (EE) and Purchase Intention (PI) were adapted from Doan (2020), Yin et al. (2016) and Venkatesh et al. (2003). The sample items for PE, EE and PI were 'Users are able to save time", "It is simple for me to purchase life insurance through my mobile phone." and "I would like to buy life insurance using my mobile phone." respectively. Some of the items were re-worded to match the demands of the current study. Apart from PE, EE and PI, the research used two control variables Age and Education. These two variables were dummy coded as previously explained.

Results

Even though the study used previously validated questionnaire items, checking the internal consistency was necessary.

Variable	**Number of items**	**Alpha coefficient**
Performance Expectancy (PE)	5	0.795
Effort Expectancy	5	0.753
Purchase Intention	5	0.875

Table 1: Cronbach's alpha coefficients

The Cronbach's alpha was determined for the 3 variables, PI, PE, and EE. The alpha coefficients for PE, EE and PI were 0.795, 0.753 and 0.875 respectively. As a rule of thumb, all the alpha coefficients were above 0.7 suggesting satisfactory internal consistency of the measures.

Correlation Analysis

A correlation matrix was requested to investigate the magnitude, strength, and direction of any pair of variables' relationship. The results are shown in table 2 below.

Correlations					
Spearman's rho	PE		PE	EE	PI
		Correlation Coefficient	1.000	.607**	.874**
		Sig. (2-tailed)	.	.000	.000
		N	250	250	250
	EE	Correlation Coefficient	.607**	1.000	.694**
		Sig. (2-tailed)	.000	.	.000
		N	250	250	250
	PI	Correlation Coefficient	.874**	.694**	1.000
		Sig. (2-tailed)	.000	.000	.
		N	250	250	250

Table 2: Correlation matrix

** Correlation is significant at the 0.01 level (2-tailed)

The correlation matrix shown above serves two functions. It was initially used to determine the nature and strength of the relationship that existed between the independent variables (PE and EE) and the dependent variable (PI). A significant moderately strong correlation between PE and EE was observed. Chances are high that the two variables move in the same direction with regards to mobile life insurance purchase decisions of customers. Both PE and EE have a significant positive influence on PI ($p < 0.01$) and can be used in regression analysis to determine the respective slope coefficients. Second, the matrix was used to assess collinearity between the final model's two main independent variables. Since the correlation coefficient of 0.607 ($p < 0.01$) was less than 0.8, the study observed that the two measures were independent. However, to clear the doubt, collinearity statistics were requested, and the results are shown in table 3 below.

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Model		Collinearity Statistics	
		Tolerance	VIF
1	Age	1.000	1.000
2	Age	.966	1.004
	Edu	.996	1.004
3	Age	.963	1.038
	Edu	.980	1.020
	PE	.595	1.685
	EE	.616	1.624

a. Dependent Variable: PI

Table 3: Collinearity statistics

According to Leech et al. (2013), when commenting on the collinearity statistics, one can use either the Tolerance or VIF. Collinearity is absent if the Tolerance is less than 1-R2. In our case, the variables had tolerance levels above 0.101 (1-0.899). Consequently, collinearity was not an issue. Thus, all variables were used in the final model.

Model Fit Results and Interpretation

The method of analysis used in IBM SPSS v 26 was Enter, which allowed simultaneous determination of the slope coefficients for the requested variables. As suggested earlier, 3 blocks of models were run to observe changes in the R-Square and F-statistics. The overall model fit results are shown in table 4 below.

Model Summary

					Change Statistics				
Model	R	R. Square	Adjusted R Square	Std. Error of the Estimates	R Square Change	F Change	Dfl	df2	Sig. F Change
1	.332	.110	.107	3.294	.110	30.773	1	2.48	.000
2	.354	.126	.119	3.272	.015	4.301	1	247	.039
3	.921	.847	.845	1.3/2	.722	579.776	1	245	.000

a. Predictors: (Constant), Age

b. Predictors: (Constant), Age, Edu
c. Predictors: (Constant), Age, Edu, EE, PE

Table 4: Model Summary

Table 4 above has three models. Model 1 used Age as the predictor of PI. Model 2 used Age and Education as predictors. Finally, model 3 used Age, Edu together with PE, EE as predictors of PI. The R-Square change for models 1 to 3, tells us how much the R-Square changes when new predictors are added in the subsequent steps while the F-change and Sig of F-Change shows if the change is statistically significant (Leech et al., 2013). In our case, the R-Square changes were 0.015 (1.5%) and 0.772 (77.1%) from model 1 to2, and model 2 to 3, respectively. As reflected by the F-changes, (30.77, $p<0.01$; 4.302, $p<0.05$; & 579.77, $p<0.01$), adding more predictors to the hierarchy improved model estimation power. As a result, model 3 was selected for analysis and discussion of the results. Focusing on model 3 adjusted R-Square, it can be observed that about 0.845 (84.5%) of the variation in PI was due to average changes in the predictor variables. Table 5 below presents the results of the analysis of variance (ANOVA).

Analysis of Variance (ANOVA)

Model		**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig**
1	Regression	333.824	1	333.824	30.773	.000
	Residual	2690.276	248	10.848		
	Total	3024.100	249			
2	Regression	379.872	2	189.936	17.742	.000
	Residual	2644.228	247	10.705		
	Total	3024.100	249			
3	Regression	2562.860	4	640.715	340.333	.000
	Residual	461.240	245	1.883		
	Total	3024.100	249			
a. Dependent Variable: PI						
b. Predictors: (Constant), Age						
c. Predictors: (Constant), Age, Edu						

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d. Predictors: (Constant), Age, Edu, EE, PE

Table 5: ANOVA Results

Table 5 presented above shows the analysis of variance together with the overall F-statistic for all the models 1 and 2. The overall F-Statistics were 30.77 ($p < 0.01$), 17.74 ($p <0.01$) and 340.33 ($p < 0.01$) for models 1, 2 and 3 respectively. As alluded to earlier, model 3 had the highest F-statistic and hence better statistical power.

Hierarchical Multiple Linear Regression Results

Model		**Unstandardized Coefficients**		**Standard Coefficients**		
		B	Std. Error	Beta	**t**	**Sig.**
1	(Constant)	19.436	.278		69.822	.000
	Age	2.328	.420	.332	5.547	.000
2	(Constant)	19.093	.322		59.291	.000
	Age	2.274	.418	.325	5.445	.000
	Edu	.871	.420	.124	2.074	.039
3	(Constant)	2.998	.506		5.928	.000
	Age	1.230	.178	.176	6.905	.000
	Edu	.414	.178	.059	2.330	.021
	PE	.660	.032	.674	20.836	.000
	EE	.254	.030	.268	8.438	.000

Table 6: Estimated regression models and coefficients

Table 6 shows the regression coefficients for the research study. Since model 3 has been adopted, the coefficients for this model together with the significance levels are discussed in this section. The standardised and unstandardized coefficients, t-statistics, and significance levels are all provided. Equation (1) can be reduced to equation (2) below using unstandardized coefficients.

$$PI = 2.99 + 1.23Age + 0.41Edu + 0.66PE + 0.25EE \ldots\ldots\ldots (2)$$

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The relationships shown by the slope coefficients are explained and discussed below. In each case, the hypotheses were either confirmed or rejected.

Discussion

PE had a regression coefficient of 0.66 with p-value < 0.01. Based on these findings, the hypothesis that PE has a significant positive impact on purchase intentions could not be rejected. This study argues that clients who find using mobile phones as a time saver and an aid to quick decision making are more likely to purchase insurance products using mobile technology than those which do not. Therefore, after controlling for age and education, an increase in PE by one unit would increase the average purchase intention by 0.66 units. The findings are consistent with those of other researchers. For example, Venkatesh et al. (2003) found PE to have a positive impact on technology adoption. Sarfaraz (2017) found PE to significantly influence consumers' mobile banking adoption. Méndez-Aparicio et al. (2017) discovered the significance of PE in customers' intentions to recommend the company's products/services to other users prior to using them themselves. PE has a significant impact on insurance managers' adoption of mobile technology (Naicker and Van der Merwe, 2018), whereas Jiang et al. (2019) discovered that consumers' intention to purchase life insurance online is significantly influenced by performance expectancy. It is the study's conclusion that consumers are likely to use their mobile gadgets to buy life insurance if they perceive that the mobile sales platform will be effective, productive, and useful. The study also supports the findings of a recent survey by Swiss Re (2020), confirming insurance consumers' increased willingness to purchase life insurance through digital platforms due to the prevailing COVID-19 pandemic conditions.

EE had a statistically significant regression coefficient of 0.25, with p-value < 0.01. The hypothesis that effort expectancy has a significant positive impact on purchase intentions could not be rejected. After controlling for age and education, a unit change in EE would increase the average purchase intention changing by 0.25 units. Therefore, it can be suggested that purchasing life insurance using mobile technology is significantly influenced by effort expectancy. Learning to use and actual operation of mobile applications should therefore be easy since this is likely to increase purchase intentions. The findings agree with Venkatesh et al. (2003) who found EE to have a positive impact on technology adoption. In addition, Sarfaraz, (2017) and Nasri and Charfeddine (2012) found EE to be significant in mobile banking adoption. Additionally, Jiang et al. (2019) established that EE has a significant positive impact on online life insurance purchase intentions. The research concluded that traditional life insurance consumers are more likely to purchase insurance through their mobile gadgets if they perceive that the process would be easy and require little effort.

The study also established that in Zimbabwe, the youths (18 and 35 years) are more likely to purchase life insurance through mobile phones than their older counterparts (p < 0.01). Resultantly, the hypothesis that purchase intentions for the young are significantly higher than for the old could not be rejected. The findings are in in line with other studies such as, (Boonsiritomachai & Pitchayadejanant, 2017; Dougherty & Clarke, 2018; Rony, 2019). The findings did not agree with the studies of Eze et al., (2011) who suggested otherwise. Insurers should introduce new products or improve existing products to address the needs of this market segment composed of the youths. Furthermore, the insurer's marketing communication effort should not neglect the needs of the elderly though they may be slower adopters of mobile insurance.

The study established that the purchase intentions of holders of at least a bachelor's degree were significantly higher than holders of lower qualifications ($p < 0.05$). Resultantly, the hypothesis that purchase intentions for those holding a bachelor's degrees and above are significantly higher than for those with lower qualifications could not be rejected. These results are consistent with suggestions by (Munusamy et al., 2013; Jiang et al., 2019; Abayomi et al., (2019) who reported that education is a significant predictor of purchase intentions. Chances are high that Zimbabwe enjoys a high literacy rate. People who can read and write better understand the importance of purchasing life insurance products using mobile devices coupled with high mobile penetration in Zimbabwe, literacy levels are an important ingredient across the spectrum and therefore should be taken advantage of.

This study examined the factors influencing mobile life insurance purchase intentions in Zimbabwe, focusing on performance expectancy and effort expectancy as outlined in the Unified Theory of Acceptance and Use of Technology (UTAUT) framework. The traditional face-to-face life insurance distribution model has faced considerable challenges during the COVID-19 pandemic, prompting the need for digital alternatives. Given this context, mobile technology has emerged as a promising channel for life insurance distribution.

Summary of Findings

The research gathered data from 250 customers of a leading life assurance firm in Zimbabwe through an online survey using a five-point Likert scale. Hierarchical multiple linear regression analysis revealed that both performance expectancy and effort expectancy significantly influence mobile life insurance purchase intentions. The analysis controlled for age and education to ensure accurate results.

The findings indicate that customers who perceive mobile insurance platforms as effective and easy to use are more likely to purchase life insurance through these channels. Performance expectancy had a stronger impact, indicating that consumers value mobile platforms that improve efficiency and productivity. Effort expectancy also played a crucial role, suggesting that simplified and user-friendly mobile interfaces encourage adoption.

The study also found that younger and more educated consumers are more inclined to use mobile devices for purchasing life insurance. This aligns with previous research indicating that younger individuals are generally more comfortable with technology (Boonsiritomachai & Pitchayadejanant, 2017). Educated consumers demonstrated a stronger inclination to adopt mobile platforms, possibly due to greater awareness and familiarity with digital tools.

Theoretical Implications

This study contributes to the literature by validating the role of performance expectancy and effort expectancy in mobile insurance adoption. Unlike previous studies that focused on mobile banking or e-commerce, this research highlights the significance of these factors within the life insurance sector. The study also affirms the relevance of the UTAUT framework in understanding digital adoption in emerging markets. Future research could explore the role of other constructs such as social influence or cultural factors in mobile insurance uptake.

Practical Recommendations

To increase mobile life insurance adoption, insurers should consider the following:

- Simplify Mobile Interfaces: Make applications easy to navigate to enhance user experience.
- Highlight Platform Effectiveness: Demonstrate how mobile platforms save time and simplify purchasing.
- Target Younger Audiences: Focus marketing efforts on digital channels popular with younger users.
- Educate Consumers: Develop content that highlights the advantages of mobile insurance to leverage Zimbabwe's high literacy rate.
- Engage Older Customers: Provide assistance through accessible support channels to reduce reluctance.
- Personalised Marketing: Tailor messages to reflect individual preferences to enhance engagement.
- Strengthen Data Security: Build trust by ensuring personal information is securely managed.

The study concludes that performance expectancy and effort expectancy are key determinants of mobile life insurance purchase intentions in Zimbabwe. Insurers should develop intuitive, effective mobile solutions while targeting younger, literate demographics through strategic marketing. Future research should examine additional factors influencing adoption, such as cultural attitudes and social influence, to provide a comprehensive understanding of consumer behaviour in digital insurance contexts.

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