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Life Insurance Ownership Factors: Lapse Status and Insurance Literacy Consideration in Klang Valley

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Abstract

This study explores the factors influencing life insurance ownership in Klang Valley, focusing on the impact of policy lapse status. Life insurance is a critical component of financial planning, yet many policies lapse each year, posing challenges for policyholders and insurers. This research examines a range of socio-economic, demographic, and behavioral factors that contribute to life insurance ownership while also analyzing how these factors correlate with the likelihood of policy lapse. Using a combination of quantitative surveys and statistical analysis, the study investigates variables such as income category, age, education, employment status, and number of households. Apart from that, an insurance literacy construct was developed and will be considered as one of the factors in determining life insurance ownership. The study shows that insurance literacy is essential to perceived benefits and trust levels, especially among policyholders who are not lapsed. A multi-group analysis also indicates that the relationship between insurance literacy and perceived risk and trust levels is statistically different regarding lapsed versus non-lapsed policyholders. The findings provide valuable insights for insurers, suggesting targeted strategies to enhance policyholder retention and improve overall market penetration in Klang Valley.

Keywords: life insurance; policy lapse; insurance literacy; ownership

1. Introduction

Life insurance is a vital financial tool that offers protection and long-term security for individuals and their families. Despite numerous national initiatives aimed at raising awareness and accessibility, such as the "Perlindungan Tenang" initiative by the Life Insurance Association of Malaysia (LIAM), Malaysia continues to experience suboptimal life insurance penetration rates (LIAM, 2020). While the total number of active policies and new premiums has grown over the past decade, the country still lags behind developed Asian economies such as Singapore, Hong Kong, and Taiwan in terms of per capita insurance premium spending and policy ownership (Swiss Re Institute, 2022). A particularly persistent issue in the Malaysian insurance landscape is the high rate of policy lapsation, which poses significant challenges not only to policyholders' financial stability but also to the operational sustainability of insurers (Milhaud et al., 2011; Subashini & Velmurugan, 2015).

Recent literature emphasizes the importance of behavioural and socioeconomic determinants in shaping individuals' insurance ownership and maintenance decisions. Factors such as trust in insurance providers, perceived benefits and risks, and attitudes toward insurance have significantly influenced consumer behaviour (Aziz et al., 2019; Chee & Sin, 2020; Sanjeewa et al., 2019). However, one critical but often overlooked component in the insurance decision-making process is insurance literacy. This concept extends beyond general financial literacy to include specific knowledge about policy rights, responsibilities, product features, risk disclosures, and claim procedures (Driver et al., 2018; Tennyson, 2011).

While previous studies have explored financial literacy in relation to insurance decisions, few have isolated insurance literacy as a distinct construct. Moreover, even fewer have analysed how insurance literacy interacts with behavioural and demographic variables influencing ownership and policy lapse. The descriptive phase of the current study has addressed this gap by developing and validating a comprehensive insurance literacy construct comprising five dimensions: knowledge of rights, duties, risk management strategies, product benefits, and potential risk disclosures (Shamsuddin et al., 2025). Results from the initial analysis indicate significant correlations between insurance literacy and intention to purchase insurance, suggesting that deeper literacy could mitigate policy lapse and improve long-term ownership rates.

Although these studies provide a base, an important synthesis indicates a strong emphasis on socio-economic drivers, more than a focus on the cognitive and knowledge-based processes that underpin the decision to lapse. Additional existing studies also tend to conceptualize financial literacy as a unitary concept, without regard to the domain-specific aspects of insurance literacy. The present study directly addresses these gaps, not only isolating insurance literacy as a distinct, multidimensional construct, but also publicly measuring the way insurance literacy mediates and moderates the relationship between consumer psychology and lapse behaviour.

To advance these findings, the present study employs Partial Least Squares Structural Equation Modelling (PLS-SEM) with Multi-Group Analysis (MGA) to investigate the structural relationships among behavioural factors, insurance literacy, and life insurance ownership and Lapse in Klang Valley. This region is particularly significant given its high insurance agent density and diverse socioeconomic composition (LIAM, 2020; Malaysian Communications and Multimedia Commission, 2020). By incorporating MGA, the study further aims to uncover group-specific differences in key pathways, particularly across income groups and lapse history segments.

This article contributes to the insurance literature in three major ways. First, it offers empirical validation of a novel, multi-dimensional insurance literacy construct. Second, it explores the mediating role of insurance literacy in behavioural models of intention to purchase insurance. Third, it identifies critical group differences that can inform more targeted policymaking and consumer education initiatives. The study provides a deeper understanding of the mechanisms driving life insurance ownership and lapsation, with important implications for insurers, regulators, and financial literacy educators.

2. Literature Reviews

This section brings together the fundamental literature on life insurance behavior into three interrelated sections: (1) socio-demographic predictors of insurance ownership and insurance lapse, (2) the newer notion of insurance literacy as its own cognitive consideration, and (3) methods to assess group differences. A review of these lines of research illustrates a substantial gap: socio-demographic factors are well understood, but cognitive and knowledge-based processes and how these processes differentially relate to consumers based on their lapse experiences are not yet well understood.

2.1 Socio-Demographic Predictors of Insurance Ownership and Insurance Lapse in Malaysia

Significant research in both Malaysia and around the world has demonstrated that life insurance ownership and lapse are influenced by factors including income, age, education, and marital status (Yaacob & Jaafar, 2017; Nor et al., 2020). In the Malaysian context, studies consistently highlight affordability and financial pressure as chief drivers of policy lapse (Kassim et al., 2019). However, a contrasting scenario arises while one would expect lower-income groups (e.g., the B40) to have the highest lapse rates due to affordability constraints, initiatives such as micro-takaful appear to improve retention among these very groups. This paradox suggests that a purely socio-economic model is insufficient and that behavioral considerations, such as insurance literacy, may interact with demographics in complex ways that have not been fully considered in previous studies.

A dual focus on both ownership and lapse provides a more complete picture of consumer engagement with life insurance. While socio-economic predictors are common to both behaviors, the decision to lapse is often shaped by more dynamic and behavioral factors, including financial literacy, perceived value of the policy, and trust in insurers.

2.2 From Financial Literacy to Insurance Literacy

The concept of financial literacy has been widely studied, but insurance literacy is more specific and has only recently gained traction as a distinct area of inquiry. Insurance literacy can be defined as an individual's knowledge, ability, and confidence to evaluate insurance needs, understand policy terms, and make informed decisions about purchase and maintenance (OECD, 2017). It involves cognitive, behavioural, and attitudinal components that go beyond basic financial knowledge.

In the Malaysian context, insurance literacy remains relatively low, particularly among lower-income and less-educated groups. Studies by Mahdzan and Tabiani (2013) and Kamaruddin et al. (2021) highlighted a critical gap in consumers' understanding of policy mechanisms, premium structures, and claim procedures. This gap often leads to underinsurance, misinformed policy choices, and lapses. While general financial literacy has been studied extensively, the concept of insurance literacy remains underexplored in empirical insurance research. Insurance literacy encompasses understanding of policy rights and responsibilities, coverage limits, claim procedures, and disclosure requirements (Tennyson, 2011). Emerging studies reveal that low insurance literacy is a major barrier to adopting and retaining life insurance (Driver et al., 2018; Sanjeewa et al., 2019).

A recent descriptive study by Shamsuddin et al. (2025) introduced and validated a multidimensional insurance literacy construct comprising five key domains: knowledge of policyholder rights, responsibilities, risk management strategies, product benefits, and potential risk disclosures. The study found significant correlations between this literacy construct and intention to purchase life insurance, suggesting its critical role in insurance behaviour models.

Importantly, a multidimensional notion of insurance literacy places it as an important mediating variable between behavioural antecedents and insurance-related outcomes. For example, an individual may have a positive attitude towards insurance, but he or she may not wish to purchase a policy owing to a lack of understanding of the benefits of the policy or the exclusions. The study by Shamsuddin et al. (2025), which illustrates significant correlations with their multidimensional construct and purchase intention, supports its importance. This suggests that if specific domains of insurance are enhanced, insurers and policymakers can alleviate lapses along with promoting other knowledgeable ownership decisions (Sinha et al., 2011), a pathway we are exploring structurally in this study.

2.3 Previous Methods

The methodological approaches used in life insurance studies vary widely, ranging from descriptive statistics and logistic regression to more advanced multivariate models. While earlier studies often relied on binary logistic models to predict insurance ownership, these models typically assume linearity and homogeneity in relationships across groups, which may overlook the differential effects of predictors among subpopulations (e.g., active vs. lapsed policyholders).

Demographic factors such as income level, education, and lapse history may moderate the strength or direction of the relationships between behavioural factors and insurance outcomes. For example, individuals in lower-income (B40) groups may be more risk-averse and sensitive to cost concerns, potentially weakening the influence of perceived product benefits (Chee & Sin, 2020). Similarly, past lapse experiences may impact consumer trust and reduce purchase intention despite high literacy levels.

To better capture these nuanced differences, Multi-Group Analysis (MGA) within the PLS-SEM framework has become increasingly popular. MGA allows researchers to test whether path coefficients differ significantly across predefined groups, thereby providing tailored insights for policy intervention and product design (Hair et al., 2022). In the context of this study, MGA will be used to assess whether the influence of behavioural and literacy factors on purchase intention varies across income and lapse-status groups.

In conclusion, the literature thoroughly covers socio-demographic drivers but does not have a distinct, detailed exploration of the interplay between cognitive factors (insurance literacy), attitude (trust, risk, and attitude), and how these relationships are moderated by a consumer's previous experience with a policy lapse. This study attempts to fill this void by introducing a validated, multi-dimensional insurance literacy construct and employing MGA to evaluate essential differences in decision-making models for lapsed policyholders versus non-lapsed policyholders.

3. Hypothesis Developments

This section will further discuss the relevant theoretical foundations and citations to support each hypothesis based on proposed PLS-SEM model.

3.1 Insurance Literacy and Its Dimensions

Insurance literacy is a multi-dimensional construct encompassing individuals' understanding of their rights, duties, product benefits, potential risks, and strategies related to insurance (OECD, 2017; Giri, 2018). In this study, insurance literacy is conceptualized as a higher-order construct composed of five reflective dimensions: knowledge on duties, rights, product benefits, potential risks, and risk strategies.

Knowledge on duties refers to consumers' awareness of their obligations within an insurance contract, such as timely premium payments or disclosure of material information. This knowledge promotes responsible insurance behavior and is essential to fostering comprehensive insurance literacy (Tan & Lee, 2019). Knowledge on rights involves understanding entitlements such as claim benefits, the right to cancel policies, and regulatory protections. This dimension enhances consumers' confidence and decision-making in insurance contexts (Lusardi & Mitchell, 2014).

Knowledge on product benefits pertains to individuals' comprehension of the advantages and features of insurance products. This knowledge empowers consumers to evaluate policy usefulness (Kaur & Singh, 2020). Similarly, knowledge on potential risks involves awareness of coverage limitations, policy exclusions, and uncertainty management, helping consumers make informed choices (Hung et al., 2009). Lastly, knowledge on risk strategy reflects consumers' understanding of when and

how to apply insurance as a financial risk mitigation tool. It equips individuals with decision-making competence in selecting appropriate insurance products (Tennyson, 2011).

3.2 Insurance Literacy and Perception Variables

Individuals with higher levels of insurance literacy are better equipped to assess both the benefits and the risks associated with insurance products. They are more likely to evaluate products based on factual knowledge rather than misconceptions, which affects their perception and purchasing decisions. Based on the Knowledge-Attitude-Behavior (KAB) model, which sequentially places knowledge impacts attitudes, which then affect behavior, we hypothesize that a higher level of insurance literacy will lead to a more accurate representation of an insurance product perception.

- H_1: Insurance literacy positively influences perceived product benefits.
- H_2: Insurance literacy negatively influences perceived product risks.

Insurance literacy also builds cognitive trust in the insurance system by reducing ambiguity and increasing transparency (Guiso et al., 2008; OECD, 2021). This trust translates into greater belief in the industry's reliability and ethical conduct. Based on the literature linking knowledge to institutional trust (Guiso et al., 2008), we propose that insurance literacy positively influences trustful belief on insurance.

- H_3: Insurance literacy positively influences trustful belief on insurance.

Furthermore, well-informed individuals are more likely to form favourable attitudes toward insurance, as understanding the function and value of insurance enhances its perceived relevance and necessity (Ajzen, 1991).

- H_4: Insurance literacy positively influences favourable attitudes toward insurance.
- H_5: Insurance literacy positively influences intention to purchase insurance.

3.3 Perception, Attitudes, and Purchase Intention

According to the Theory of Planned Behaviour (Ajzen, 1991), behavioural intention is influenced by attitudes, subjective norms, and perceived behavioural control. In insurance, perceived product benefits increase consumers' motivation to purchase, whereas perceived risks, such as loss of premium or claim rejection, act as deterrents.

- H_6: Perceived product benefits positively influence intention to purchase insurance.
- H_7: Perceived product risks negatively influence intention to purchase insurance.

Trust is a central construct in financial decision-making, especially in insurance, where intangible services are delivered over time. A high level of trust in insurance providers promotes positive behavioural intentions (Ennew & Sekhon, 2007).

- H_8: Trustful belief on insurance positively influences intention to purchase insurance.

Favourable attitudes reflect a positive evaluation of insurance and its role in financial planning, which is a direct antecedent of purchase intention in consumer behaviour models (Ajzen, 1991; Fishbein & Ajzen, 2010).

- H_9: Favourable attitudes toward insurance positively influence intention to purchase insurance.

3.4 MGA Hypothesis for Purchase Intention

Insurance literacy influences consumers' understanding of insurance mechanisms, benefits, and rights (OECD, 2017). Individuals who have previously lapsed may have experienced dissatisfaction, misunderstanding, or financial strain, which could weaken the positive impact of insurance literacy on their intention to repurchase. In contrast, those with active policies may convert literacy into stronger

purchase intentions due to continued trust and engagement with insurers (Abreu & Mendes, 2020; Khan et al., 2022).

- H_{10}: The effect of insurance literacy on intention to purchase insurance differs significantly between individuals who have lapsed and those who have not.

As for the perceived product benefits, such as financial protection, peace of mind, and income replacement, these are core drivers of purchase intention (Homburg et al., 2009). However, individuals who have lapsed may evaluate these benefits with greater skepticism or undervalue them due to prior unmet expectations. Therefore, the influence of perceived benefits may be weaker compared to non-lapsed individuals who likely continue to perceive value in insurance coverage. According to Rahim et al. (2019) and Lee and Chen-Yu (2021), perceived product value strongly impacts repurchase decisions but is mitigated by past service experience.

- H_{11}: The effect of perceived product benefits on intention to purchase insurance differs significantly between the two groups.

Meanwhile, perceived risks include concerns over denied claims, policy exclusions, or premium loss. Lapsed individuals may have higher risk sensitivity, possibly due to negative experiences or financial pressures, which would magnify the negative impact of perceived risks on purchase intention. On the other hand, active policyholders may discount perceived risks due to brand familiarity or prior claim satisfaction (Bhatti et al., 2020; Bashir et al., 2021).

- H_{12}: The effect of perceived product risks on intention to purchase insurance differs significantly between the two groups.

Trust is crucial in insurance, as customers are often unable to evaluate product outcomes until a claim is made (Ennew & Sekhon, 2007). Individuals who have lapsed may exhibit low trust due to dissatisfaction, while active users maintain higher trust levels, which increases purchase intention. Hence, the strength of the trust-intention relationship may differ across groups (Nguyen et al., 2020; Alam & Islam, 2021).

- H_{13}: The effect of trustful belief on insurance on intention to purchase insurance differs significantly between individuals who have lapsed and those who have not.

Finally, attitudes toward insurance encompass emotional and cognitive evaluations of its usefulness and value (Ajzen, 1991). Lapsed individuals may form less favorable or ambivalent attitudes due to prior policy discontinuation, weakening the attitude-intention relationship. In contrast, satisfied policyholders maintain positive attitudes that more strongly influence their intent to continue or expand insurance coverage (Dissanayake & Weerasiri, 2019; Ali et al., 2023).

- H_{14}: The effect of favourable attitudes toward insurance on intention to purchase insurance differs significantly between the two groups.

3.5 Conceptual Framework

Drawing on the theoretical and conceptual rationales, the researcher developed the study's conceptual framework, which is depicted in Figure 1.

4. Materials and Methods

This study employed a quantitative, cross-sectional survey design to examine the structural relationships among behavioral factors, insurance literacy, life insurance ownership, and lapse. The research adopts Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS software 4.0, which is appropriate for theory development and predictive modeling in social sciences (Hair et al., 2022). Additionally, Multi-Group Analysis (MGA) was utilized to identify significant group differences based on income level and lapse status, thereby offering more granular insights into the decision-making processes of Malaysian insurance consumers.

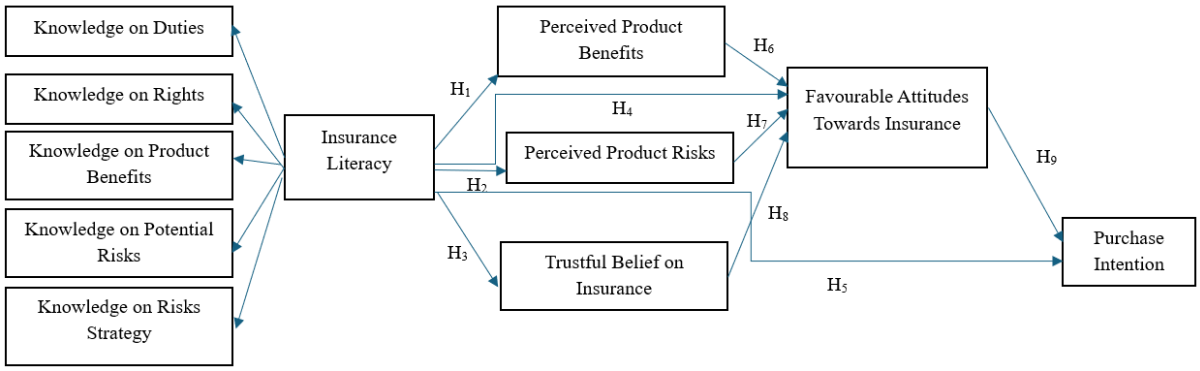

Figure 1: Research Framework

4.1 Population and Sampling

The target population comprises Malaysian citizens aged 18 to 64 years who currently own or have previously owned life insurance policies. The study focused specifically on respondents residing in the Klang Valley, including Kuala Lumpur, Selangor, and Putrajaya, due to their high life insurance agent density and internet penetration rates (Malaysian Communications and Multimedia Commission, 2020; LIAM, 2020). A purposive sampling technique was used to ensure that respondents met the following inclusion criteria; age between 18 to 64 years, current or past income earners, current or past life insurance policyholders, and residents of Klang Valley.

Data were collected through an online self-administered questionnaire, distributed with the assistance of insurance agents. Out of 269 responses received, 230 were retained for analysis after data cleaning procedures such as outlier removal, straight-lining checks, and re-coding of negatively worded items. This sample size exceeded the minimum requirement of 147 for detecting a minimum R^2 of 0.10 in the most complex construct (Hair et al., 2014). Furthermore, using GPower, the minimum sample size needed is 92 cases for the analysis. Our sample size of n = 230 is slightly more than that required to achieve a power of 0.8.

4.2 Instrument Development

The research instrument was a structured questionnaire designed to capture respondents' demographic profiles, insurance behaviour, and latent psychological constructs related to life insurance decisions. The questionnaire comprised four major sections. The first section gathered demographic information such as gender, age, marital status, income level, education level, employment sector, and residential area. The second section collected data on life insurance ownership and policy lapse history, including whether respondents currently held a life insurance policy, had ever allowed a policy to lapse, or had switched providers.

The third section measured key behavioural constructs that influence insurance purchase decisions. These constructs included attitude toward insurance (ATI), perceived product benefits (PPB), perceived product risks (PPR), trustful beliefs (TB), and intention to purchase insurance (IP). A total of 22 items were adapted from previous validated studies (Sanjeewa et al., 2019; Chee & Sin, 2020; Aziz et al., 2019) and were measured using a 7-point Likert scale ranging from 1 ("strongly disagree") to 7 ("strongly agree").

The fourth and most novel section of the instrument measured insurance literacy, which was conceptualized as a higher-order construct. This section consisted of 24 items distributed across five first-order reflective dimensions: knowledge about rights as policyholders, duties as policyholders, risk management strategies, product benefits, and potential risk disclosures. Each item used a 7-point scale

ranging from 1 ("do not understand at all") to 7 ("completely understand"). The development of this construct was guided by prior research in insurance and financial literacy (Driver et al., 2018; Sinha et al., 2011; Tennyson, 2011) and underwent a rigorous validation process.

The initial English version was translated into Malay and reviewed by language and subject-matter experts. The initial pool of items was reviewed by panel experts from academic and industry practitioners to establish content validity using Lawshe's Content Validity Ratio (CVR), followed by pilot testing (n=50) and item refinement through Rasch analysis to ensure reliability and dimensional consistency before distribution to the full sample. To deal with potential sources of bias, we took a number of precautions. To minimize social desirability bias, we ensured confidentiality and anonymity. To minimize recall bias around lapse behavior, the surveys were written with clearly worded, simple questions where respondents were asked to think about their most recent experience with the policy. To deal with sampling bias, we utilized a purposive sampling method through different insurance agencies to have a more varied selection of current and former policyholders.

4.3 Data Analysis Procedure

The collected data were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) via SmartPLS software, which is suitable for complex models with hierarchical constructs and when the primary goal is prediction rather than confirmation (Hair et al., 2014). The analysis was conducted in two major stages: assessment of the measurement model and evaluation of the structural model.

In the first stage, the measurement model was evaluated to ensure construct reliability and validity. Reliability was tested using Cronbach's alpha and composite reliability, with values above 0.70 considered acceptable. Convergent validity was assessed through the average variance extracted (AVE), with a minimum threshold of 0.50. Discriminant validity was examined using the Heterotrait-Monotrait (HTMT) ratio of correlations, where values below 0.85 indicate adequate construct separation. The hierarchical structure of the insurance literacy construct was modelled using a reflective-formative approach, where each of the five lower-order constructs was treated as reflective indicators of the higher-order construct.

In the second stage, the structural model was assessed. Path coefficients were estimated through bootstrapping with 5,000 resamples to determine the significance of hypothesized relationships. Key indicators of model quality, such as R^2 (explained variance), and f^2 (effect size) were reported for endogenous constructs. The mediating effect of insurance literacy was also tested by examining the indirect effects of behavioural variables on purchase intention through insurance literacy, using the bootstrapped confidence intervals. Bootstrapping with 5,000 resamples was used to test the stability and significance of the path coefficients. The non-parametric method is a good fit for PLS-SEM studies since it does not assume normality, while providing reliable standard errors and confidence intervals for hypothesis testing (Hair et al., 2022).

To examine whether structural paths varied across different groups, Multi-Group Analysis (MGA) was performed. Specifically, the study compared structural relationships across policies and lapse statuses (lapsed vs. non-lapsed). Prior to conducting MGA, the Measurement Invariance of Composite Models (MICOM) procedure was applied to ensure partial or full measurement invariance across groups. MGA was then conducted using both the PLS-MGA method and permutation testing to assess the significance of group differences in path coefficients. All analyses were conducted at a 5% significance level.

4.4 Ethical Consideration

Prior to data collection, ethical approval was obtained from the Research Ethics Committee of Universiti Kebangsaan Malaysia (UKM PPI/111/8/JEP-2021-544). Informed consent was sought from all participants before completing the questionnaire, and all responses were anonymized to maintain confidentiality.

5. Results and Discussions

This section outlines the research results in two primary segments: Descriptive Analysis and PLS-SEM Analysis. The descriptive analysis summarizes respondent traits and their spread across essential variables associated with life insurance possession and lapse patterns. The PLS-SEM analysis examines the structural connections among constructs and evaluates the proposed model through multi-group analysis (MGA), emphasizing differences based on income groups.

5.1 Descriptive Analysis

This subsection summarizes the demographic and socioeconomic profile of the respondents ($N = 230$), segmented by life insurance ownership and lapse status. Key variables examined include gender, ethnicity, state of residence, education level, occupational sector, marital status, and B40 income status. Table 1 shows the cross-tabulation of life insurance lapse status with socioeconomic and demographic factors.

The results reveal several important patterns. Firstly, a higher proportion of males and single individuals were found in the lapse group, whereas females and married individuals dominated the non-lapse group. Secondly, Bumiputera respondents were more likely to maintain their policies than non-Bumiputera, indicating possible cultural or religious influences in policy commitment. Next, government sector employees and pensioners showed lower lapse rates, potentially due to structured payroll deductions or post-retirement financial planning.

Table 1: Cross-tabulation of life insurance lapse status with socioeconomic and demographic factors

Variable	Description	All ($N = 230$)	Lapse *Yes* ($N = 84$)	Lapse *No* ($N = 146$)
		Freq (%)	Freq (%)	Freq (%)
Ownership	1=Yes	149 (64.8)	45 (53.6)	104 (71.2)
	0=No	81 (35.2)	39 (46.4)	42 (28.8)
Gender	1= Male	104 (45.2)	44 (52.4)	60 (41.1)
	2=Female	126 (54.8)	40 (47.6)	86 (58.9)
Ethnicity	1=Bumiputera	185 (80.4)	54 (64.3)	131(89.7)
	2=Others	45 (19.6)	30 (35.7)	15 (10.3)
State of Residents	1=Kuala Lumpur	88 (38.3)	34 (40.5)	54 (37)
	2=Selangor	126 (54.8)	42 (50)	84 (57.5)
	3=Putrajaya	16 (7.0)	8 (9.5)	8 (5.5)
Education	1=Professional	7 (3.0)	4 (4.8)	3 (2.1)
	2=Postgraduate	34 (14.8)	11(13.1)	23 (15.8)
	3=Undergraduate	146 (63.5)	52 (61.9)	94 (64.4)
	4=SPM/STPM/Certificate	38 (16.5)	16 (19)	22 (15.1)
	5=Others	5 (2.2)	1 (1.2)	4 (2.7)
	1=Government sector	42 (18.3)	23 (27.4)	19 (13.0)

Occupation Sector	2=Private sector	119 (51.7)	41 (48.8)	78 (53.4)
	3=Self-employed/Entrepreneur	20 (8.7)	9 (10.7)	11 (7.5)
	4=Unemployed	5 (2.2)	3 (3.6)	2 (1.4)
	5=Pensioner	24 (10.4)	4 (4.8)	20 (13.7)
	6=Others	20 (8.7)	4 (4.8)	16 (11)
Marital Status	1=Single	83 (36.1)	45 (53.6)	38 (26)
	2=Married	139 (60.4)	35 (41.7)	104 (71.2)
	3=Divorce	4 (1.7)	1 (1.2)	3 (2.1)
	4=Widow/Widower	4 (1.7)	3 (3.6)	1 (0.7)
B40 Status	1=Yes	143 (62.2)	40 (47.6)	103 (70.5)
	0=No	87 (37.8)	44 (52.4)	43 (29.5)
Lapse	1=Yes	84 (36.5)	-	-
	0=No	146 (63.5)	-	-

Note 1: Freq= frequency, %=percentage.

Furthermore, the B40 group, while generally considered financially vulnerable, exhibited stronger policy retention, possibly due to targeted microtakaful schemes or subsidized premiums. These patterns suggest that demographic and income-related factors influence insurance ownership and policy continuity, supporting the need for personalized financial education and targeted product design.

5.2 PLS-Sem Analysis

This subsection discussed the outcomes of the Partial Least Squares Structural Equation Modeling (PLS-SEM) employed to evaluate the measurement and structural models. The SmartPLS 4.0 software was used to examine the path connections among constructs like Insurance Literacy, Perceived Product Benefits, Perceived Product Risks, Trust, and Intent to Purchase Insurance. To assess the measurement and structural model, specifically SmartPLS Version 4.0 and bootstrap resampling (5,000 resamples) were used. In addition, a multi-group analysis (MGA) between the two organizations was conducted using SmartPLS. For applying MGA, the data were split into two data sets: Lapse (1) and not Lapse (0) (Lapse=1, 84 samples and Lapse=0, 146 samples). Furthermore, all other necessary criteria Hair et al. (2014) suggested were tested, i.e., convergent validity, discriminant validity, and measurement invariance.

5.2.1 Test of measurement model

5.2.2.1 Convergent validity

Convergent validity is evaluated by examining item loadings, the composite reliability of each scale, and the average variance extracted for every construct. Hair et al. (2014) recommend that standardized loadings exceed 0.707, while Fornell and Larcker (1981) suggest that AVE values should be above 0.5. The findings in Table 2 indicate that the reliability, items, and composites for both data sets significantly exceed the suggested threshold of 0.70. Moreover, the AVEs exceeded the recommended value of 0.5 by a significant margin.

5.2.2.2 Discriminant validity

Discriminant validity was also verified using the Heterotrait-Monotrait Ratio (HTMT) recommended by Henseler et al. (2015). Table 3 shows that all the HTMT indices for both Non-Lapse and Lapse groups were below the threshold value of 0.90, implying that each construct is empirically distinct from the rest. The greatest value of HTMT seen in the Lapse group was 0.841 (between ATI and PPB), whereas in the non-lapse group, the greatest was 0.898 (between ATI and TB). These indicate the validation of discriminant validity for both groups, as shown in Tables 3 and 4.

Table 2: PLS factor loadings, CR, and AVE of full and lapse samples

Constructs	Items	Full Sample (n=230)			Lapse=1 (n=84)			Lapse=0 (n=146)		
		Loading	AVE	CR	Loading	AVE	CR	Loading	AVE	CR
Insurance Literacy (IL)	KR	0.925	0.661	0.979	0.881	0.533	0.965	0.939	0.710	0.983
	KD	0.914			0.828			0.936		
	KPB	0.942			0.892			0.957		
	KPR	0.955			0.934			0.961		
	KRS	0.934			0.935			0.937		
Perceived Product Risks (PPR)	R01	0.916	0.673	0.859	0.976	0.682	0.863	0.890	0.640	0.841
	R02	0.731			0.713			0.704		
	R03	0.803			0.765			0.795		
Perceived Product Benefits (PPB)	M01	0.790	0.705	0.923	0.758	0.674	0.912	0.798	0.717	0.927
	M02	0.846			0.830			0.855		
	M03	0.793			0.794			0.789		
	M04	0.878			0.863			0.886		
	M05	0.886			0.854			0.899		
Trustful Believe (TB)	K01	0.903	0.729	0.930	0.902	0.674	0.910	0.898	0.742	0.934
	K02	0.915			0.893			0.923		
	K03	0.913			0.859			0.928		
	K04	0.821			0.814			0.820		
	K05	0.697			0.600			0.718		
Attitude (A)	S01	0.853	0.716	0.909	0.827	0.609	0.856	0.873	0.767	0.929
	S02	0.903			0.865			0.926		
	S03	0.907			0.878			0.927		
	S04	0.705			0.484			0.770		
Intention to Purchase (IP)	N01	0.835	0.678	0.913	0.766	0.661	0.906	0.858	0.688	0.916
	N02	0.731			0.824			0.709		
	N03	0.831			0.838			0.831		
	N04	0.915			0.895			0.922		
	N05	0.792			0.730			0.814		

Note 2: AVE= average variance extracted, CR= composite reliability.

Table 3: Heterotrait-monotrait ratio (HTMT) for full sample

Constructs	Discriminant validity for full sample					
	ATI	IL	IP	PPB	PPR	TB
ATI						
IL	0.721					
IP	0.863	0.721				
PPB	0.865	0.691	0.846			
PPR	0.399	0.201	0.439	0.373		
TB	0.854	0.747	0.807	0.842	0.303	

5.2.2.3 Structural Model Evaluation

Summary of Path Coefficients and Effect Sizes by Group

The hypotheses were evaluated through bootstrapping using 5,000 subsamples, assessing the path coefficients, t-values, and p-values. Table 5 summarizes the direct relationships between constructs. Most hypothesized relationships were statistically significant ($p < 0.05$), confirming the proposed structural model. Table 5 also provides a comprehensive breakdown of the structural model's path coefficients, standard errors, t-values, and effect sizes (f^2) for the full sample as well as both subsamples (Lapse=1 and Lapse=0). This detailed representation allows for better group-level comparison and interpretation of the strength and significance of relationships across different policyholder statuses. The effect sizes (f^2) for the significant paths fell in the small-medium range (0.02 to 0.25) based on Cohen's (1988) criteria, indicating that the relationships are not only statistically significant, but they also hold practical utility. To assess the robustness of the path coefficients, bias-corrected bootstrapped confidence intervals were examined. The results indicated that for all statistically significant relationships, the 95% confidence intervals excluded zero, providing strong evidence for the stability and significance of these estimates. As an example, the path from Insurance Literacy to Perceived Product Benefits (IL → PPB) for the full sample yielded a confidence interval of [0.557, 0.667], reinforcing the positive and significant influence of insurance literacy on perceived benefits.

5.2.2 Multi-Group Analysis (MGA)

5.2.2.1 Measurement Invariance Assessment (MICOM)

Step 1: Configural Invariance
Configural invariance was ensured as the measurement model structure, indicators, data treatment, and algorithm settings were kept identical across both groups (Lapse=1 and Lapse=0).

Step 2: Compositional Invariance
Compositional invariance was evaluated using a permutation test. The results confirmed that the correlation between composite scores from the two groups was close to 1, and the confidence intervals for each construct's path coefficient did not include zero as presented in Table 6.

Step 3: Equality of Composite Mean Values and Variances
As shown in Table 7, most constructs did not exhibit significant differences in means and variances across the two groups. Therefore, partial measurement invariance is confirmed. Since Steps 1 and 2 were established, and Step 3 showed partial support, partial measurement invariance is confirmed. This permits valid Multi-Group Analysis (MGA).

5.2.2.2 Bootstrapping Results by Group

Bootstrapping with 5,000 resamples was conducted separately for both groups to assess the reliability of path coefficients. The significance was determined using the t-statistics and p-values. A t-value > 1.96 and $p < 0.05$ indicates statistical significance at the 5% level, as depicted in Table 8 below. The findings give insight into the different ways the relationships between insurance literacy, perceptions, attitudes, and intention to purchase vary between segments of customers.

Table 4: Heterotrait-monotrait ratio (HTMT) for Lapse=1 and Lapse=0

Constructs	Discriminant validity for Lapse=1						Discriminant validity for Lapse=0					
	ATI	**IL**	**IP**	**PPB**	**PPR**	**TB**	**ATI**	**IL**	**IP**	**PPB**	**PPR**	**TB**
ATI												
IL	0.551						0.767					
IP	0.798	0.630					0.885	0.751				
PPB	0.841	0.549	0.748				0.868	0.734	0.882			
PPR	0.171	0.184	0.174	0.201			0.508	0.318	0.601	0.494		
TB	0.716	0.576	0.652	0.732	0.142		0.898	0.813	0.877	0.887	0.438	

Table 5: Summary of structural paths by group

Path	Full sample					Lapse=1					Lapse=0				
	Std. Beta	**SE**	***t*-value**	**f²**	**95% CI**	**Std. Beta**	**SE**	***t*-value**	**f²**	**95% CI**	**Std. Beta**	**SE**	***t*-value**	**f²**	**95% CI**
IL → PPB	0.612	0.028	7.456**	0.243	[0.557, 0.667]	0.533	0.031	6.123**	0.187	[0.472, 0.594]	0.692	0.032	7.873**	0.221	[0.629, 0.755]
IL → PPR	0.378	0.035	5.983**	0.187	[0.309, 0.447]	0.044	0.045	0.976	0.005	[-0.044, 0.132]	-0.330	0.041	5.530**	0.192	[-0.410, -0.250]
IL → TB	0.502	0.026	8.320**	0.214	[0.451, 0.553]	0.547	0.033	7.304**	0.148	[0.482, 0.612]	0.776	0.030	8.605**	0.273	[0.717, 0.835]
IL → ATI	0.228	0.034	1.730	0.062	[-0.038, 0.494]	0.090	0.040	2.250	0.021	[-0.018, 0.198]	0.158	0.039	3.098**	0.045	[0.082, 0.234]
IL → IP	0.361	0.031	6.109**	0.142	[0.300, 0.422]	0.256	0.028	4.221**	0.096	[0.201, 0.311]	0.130	0.037	2.945**	0.061	[0.057, 0.203]
PPB → IP	0.295	0.027	6.214**	0.189	[0.242, 0.348]	0.248	0.030	4.976**	0.110	[0.189, 0.307]	0.254	0.029	5.612**	0.134	[0.197, 0.311]
PPR → IP	-0.207	0.032	3.300**	0.071	[-0.270, -0.144]	-0.125	0.035	1.786	0.022	[-0.194, -0.056]	-0.170	0.036	4.148**	0.067	[-0.241, -0.099]
TB → IP	0.342	0.029	5.470**	0.163	[0.285, 0.399]	0.109	0.034	1.960	0.037	[0.042, 0.176]	0.208	0.030	5.168**	0.088	[0.149, 0.267]
ATI → IP	0.418	0.025	7.881**	0.248	[0.369, 0.467]	0.270	0.026	5.923**	0.109	[0.219, 0.321]	0.260	0.027	5.964**	0.113	[0.207, 0.313]

Note 3: f^2 = effect size, **p < 0.01, *p < 0.05, CI = Confidence Interval. Significance is determined by the bootstrap confidence interval not containing zero (0)

Table 6: MICOM step 2 assessment of compositional invariance

Construct Path	Correlation	5% Quantile	95% Quantile	Permutation *p*-value	Compositional Invariance
IL	1.000	1.000	1.000	0.054	Yes
PPB	1.000	0.999	0.998	0.625	Yes
PPR	0.979	0.98	0.932	0.259	Yes
TB	0.998	0.999	0.998	0.067	Yes
ATI	0.997	0.999	0.997	0.069	Yes
IP	0.998	0.999	0.998	0.117	Yes

Table 7: MICOM step 3 equality of composite means and variances

Construct	Mean				Variance				Invariance Conclusion
	MOD (MPMD)	Confidence interval		*p*-values	VOD (VMPD)	Confidence interval		*p*-values	
		5%	95%			5%	95%		
IL	-0.198 (0.006)	-0.219	0.232	0.071	-0.684 (-0.017)	-0.424	0.369	0.002	Partial Invariance
PPB	-0.224 (0)	-0.229	0.226	0.058	-0.383 (-0.017)	-0.362	0.334	0.039	Partial Invariance
PPR	0.316 (0.006)	-0.214	0.222	0.01	0.136 (-0.009)	-0.358	0.368	0.236	Partial Invariance
TB	-0.475 (0.001)	-0.225	0.227	0	-0.304 (-0.01)	-0.389	0.351	0.1	Partial Invariance
ATI	-0.314 (0.001)	-0.229	0.215	0.013	-0.418 (-0.024)	-0.549	0.518	0.126	Partial Invariance
IP	-0.167 (-0.001)	-0.232	0.233	0.121	-0.392 (-0.019)	-0.434	0.401	0.08	Full Invariance

Note 4: MOD = mean original difference, MPMD = mean-permutation mean difference, VOD = variance original difference, VMPD = variance-permutation mean difference

For both groups, non-lapsed (Lapse=0) and lapsed (Lapse=1), the insurance literacy (IL) had a statistically significant influence on perceived product benefits (PPB) and trustful beliefs on insurance (TB), which supports H1 and H3 of the within-group structures. IL did not significantly affect perceived product risks (PPR) in the lapsed group but did in the non-lapsed group. This indicates that insurance literacy is effective at altering perceived risks for individuals who maintain their policies but not for those who lapse.

The influence of IL on intention to purchase (IP) was significant for the lapsed group, which seems to suggest a possible reactive intention when it comes to IP and insurance products after a gap in purchasing. Favourable Attitudes (ATI) in both groups (Lapse=0) and (Lapse=1) had a significant influence on IP, which indicates the importance of positive predisposition to IP irrespective of lapse.

The predictive path between PPB and IP was significant for both groups, supporting the notion that perceived benefits can influence purchase intentions. However, the paths between PPR and IP, and TB and IP were mixed as TB was only significant in the non-lapsed group (Lapse=0), while PPR was insignificant in either group. This reinforces the idea that perceived risks and trust operate in more complex ways depending on lapses.

Table 8: Bootstrapping results by group

Path	Lapse=1				Lapse=0			
	Coeff. (O)	**t −value**	**p −value**	**Significance**	**Coeff. (O)**	**t-value**	**p −value**	**Significance**
IL → PPB	0.533	> 1.96	< 0.05	Yes	0.692	> 1.96	< 0.05	Yes
IL → PPR	0.044	< 1.96	> 0.05	No	-0.330	> 1.96	< 0.05	Yes
IL → TB	0.547	> 1.96	< 0.05	Yes	0.776	> 1.96	< 0.05	Yes
IL → ATI	0.090	< 1.96	> 0.05	No	0.158	< 1.96	> 0.05	No
IL → IP	0.256	> 1.96	< 0.05	Yes	0.130	< 1.96	> 0.05	No
PPB → IP	0.248	> 1.96	< 0.05	Yes	0.254	> 1.96	< 0.05	Yes
PPR → IP	-0.125	< 1.96	> 0.05	No	-0.170	< 1.96	> 0.05	No
TB → IP	0.109	< 1.96	> 0.05	No	0.208	> 1.96	< 0.05	Yes
ATI → IP	0.270	> 1.96	< 0.05	Yes	0.260	> 1.96	< 0.05	Yes

5.3 MGA Permutation Results

Permutation-based multi-group analysis (MGA) was employed to compare the structural paths across the two groups. The MGA results in Table 9 identify whether the differences in path coefficients are statistically significant ($p < 0.05$).

Table 9: Multi-group analysis results

Hypothesis	Path	Lapse=1	Lapse=0	Difference	$p - value$	Significance
H_1	IL → PPB	0.533	0.692	-0.159	0.052	Not significant
H_2	IL → PPR	0.044	-0.330	0.374	0.002	Significant
H_3	IL → TB	0.547	0.776	-0.229	0.001	Significant
H_4	IL → ATI	0.090	0.158	-0.068	0.310	Not significant
H_5	IL → IP	0.256	0.130	0.126	0.155	Not significant
H_6	PPB → IP	0.248	0.254	-0.007	0.482	Not significant
H_7	PPR → IP	-0.125	-0.170	0.045	0.292	Not significant
H_8	TB → IP	0.109	0.208	-0.098	0.295	Not significant
H_9	ATI → IP	0.270	0.260	0.010	0.463	Not significant

6. Discussion and conclusions

The multi-group analysis (MGA) insights reveal differences in the impact of insurance literacy and related constructs on life insurance purchasing intention by lapsing status. Of the nine hypothesized relationships, only the paths for H_2 (Insurance Literacy → Perceived Product Risks) and H_3 (Insurance Literacy → Trustful Belief in Insurance) revealed statistically significant group differences. In terms of these paths, the effect of insurance literacy on perceived product risk and trustful beliefs was greater for the non-lapsed group (Lapse=0), suggesting that insurance literacy may be more effective at lowering perceived risk and eliciting trust for those not lapsed. This supports previous literature, which indicates that insurance literacy plays a key role in risk perception and trust formation (Lin et al., 2017; Li & Moshirian, 2021).

As for the H_{10} to H_{14}, none of the moderation hypotheses were supported in the MGA results. The path differences for Intention to Purchase Insurance between the lapsed and non-lapsed groups were all statistically non-significant ($p > 0.05$). This indicates that although the antecedents like insurance literacy, trust, and attitudes may influence purchase intention, they do so in a similar way across policy status groups. Hence, these constructs seem to operate similarly for respondents regardless of whether they have previously lapsed in insurance.

While not statistically significant at the usual 0.05 cut-off point, H_1 (Insurance Literacy → Perceived Product Benefits) had a close to significant difference ($p = 0.052$), suggesting that insurance literacy has a moderately larger effect on perceived product benefits for non-lapsed policyholders than for lapsed policyholders. While the effect was greater for the non-lapsed group, the difference was insignificant. Similarly, hypotheses H_4 through H_9 did not approach significant path differences. Together, these results show stable measurement and effects in perceived benefits, perceived risks, attitude, and trust on purchase intention of life insurance, regardless of Lapse.

This indicates that while insurance literacy differentially affects certain psychological drivers such as perceived risk and trust, its downstream effect on purchase intention is somewhat homogenous across all groups. The lack of significant differences between H_5 and H_9 suggests that once perceptions and attitudes are formed, the subsequent influence on intention to purchase may be stable regardless of the history of policy lapse.

The implications for theory and practice are substantial. Theoretically, explicitly validating a multidimensional insurance literacy construct brings to the table a finer-grained instrument for the study of financial decision-making going forward. The use of an MGA elucidates that the effectiveness of literacy interventions cannot be a one-size-fits-all approach and that much will depend on the policyholder's prior experience. From a practical angle, the insurers may want to pursue the findings to develop targeted literacy programs. For customers who have not lapsed, communication may center on the reinforcement of the value of and risk-marketing benefits related to the policies. For lapse customers, campaigns may first need to focus on building trust again and addressing specific previous complaints before embarking on product communication to reactivate customers. In addition, regulators may also want to think about insurance-specific modules in national financial literacy schemes as a means of enhancing consumer capability and reducing the lapse rate that stems from misunderstanding.

In order to improve our understanding of life insurance ownership behavior, along with the limitations mentioned in this study, a number of future directions are proposed based on the findings of this study. First and foremost, expansion to different geographical contexts. The study was limited to policyholders in Klang Valley. Future work could consider applying the model in other regions of Malaysia or even countries to evaluate further how the present findings can be generalized in other socioeconomic and cultural contexts.

Secondly, the inclusion of psychological and behavioral factors. Future studies may enhance the study with the inclusion of psychological constructs such as risk aversion, financial anxiety, behavioral biases, and loss aversion. These factors may contribute to insurance lapse behavior and intention to re-engage in the future. Lastly, the inclusion of insurance literacy as a multidimensional variable. The insurance literacy construct, as defined in this study, was a brand-new construct developed and validated as part of this study. Therefore, future studies should continue to establish and validate the insurance literacy construct in other populations and potentially compare it with financial literacy to assess relative effects.

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8. References

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Alam, M. M., & Islam, M. T. (2021). Trust, satisfaction and intention in life insurance: Empirical evidence from Bangladesh. *Asian Journal of Economics and Banking*, *5*(1), 64–79. https://doi.org/10.1108/AJEB-11-2020-0088

Ali, M., Raza, S. A., & Farrukh, M. (2023). Consumer attitudes and behavioral intention toward Islamic insurance in Pakistan: The moderating role of past experiences. *International Journal of Islamic and Middle Eastern Finance and Management*, *16*(1), 1–22. https://doi.org/10.1108/IMEFM-01-2022-0023

Aziz, S., Md Husin, M., Hussin, N., & Afaq, Z. (2019). Factors that influence individuals' intentions to purchase family Takaful: Mediating role of perceived trust. *Asia Pacific Journal of Marketing and Logistics*, *31*(1), 81–104. https://doi.org/10.1108/APJML-12-2017-0311

Bank Negara Malaysia. (2022). *Financial stability review – Second half 2022*. https://www.bnm.gov.my/documents/20124/8293290/fsr2022h2_en_book.pdf

Bashir, S., Mehreen, A., & Albarq, A. N. (2021). Insurance adoption in the emerging market: A consumer perception-based study. *Journal of Public Affairs*, *21*(1), Article e2210. https://doi.org/10.1002/pa.2210

Bhatti, A., Alam, M. N., & Arshad, M. (2020). Predicting the consumers' purchase intention of life insurance: Evidence from Pakistan. *International Journal of Academic Research in Business and Social Sciences*, *10*(8), 148–166. https://doi.org/10.6007/IJARBSS/v10-i8/7521

Chee, L. C., & Sin, T. S. (2020). The significance of personal value, risk attitude and trust on life insurance ownership in the northern regions of Malaysia. *Jurnal Pengurusan*, *58*, 67–79. https://doi.org/10.17576/pengurusan-2020-58-06

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.

Dissanayake, D. M. R., & Weerasiri, S. (2019). Factors affecting the behavioral intention to select life insurance policies: Evidence from Sri Lanka. *International Journal of Academic Research in Accounting, Finance and Management Sciences*, *9*(1), 52–62. https://doi.org/10.6007/IJARAFMS/v9-i1/5827

Driver, T., Brimble, M., Freudenberg, B., & Hunt, K. (2018). Insurance literacy in Australia: Not knowing the value of personal insurance. *Financial Planning Research Journal*, *1*(1), 53–76.

Ennew, C. T., & Sekhon, H. (2007). Measuring trust in financial services: The trust index. *Consumer Policy Review*, *17*(2), 62–68.

Fishbein, M., & Ajzen, I. (2010). *Predicting and changing behavior: The reasoned action approach*. Psychology Press.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50. https://doi.org/10.1177/002224378101800104

Giri, M. (2018). *A behavioral study of life insurance purchase decisions* (Doctoral dissertation, Indian Institute of Technology Kanpur). IITK Research Repository.

Guiso, L., Sapienza, P., & Zingales, L. (2008). Trusting the stock market. *The Journal of Finance*, *63*(6), 2557–2600. https://doi.org/10.1111/j.1540-6261.2008.01408.x

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2014). *A primer on partial least squares structural equation modeling (PLS-SEM)*. SAGE Publications.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). Sage Publications.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Homburg, C., Koschate, N., & Hoyer, W. D. (2009). The role of cognition and affect in the formation of customer satisfaction: A dynamic perspective. *Journal of Marketing*, *73*(3), 21–37. https://doi.org/10.1509/jmkg.73.3.21

Hung, A., Parker, A. M., & Yoong, J. (2009). *Defining and measuring financial literacy* (Working Paper No. WR-708). RAND Corporation. https://www.rand.org/pubs/working_papers/WR708.html

Kamaruddin, S. N., Jusoh, M. S., & Hussin, M. Y. M. (2021). Understanding life insurance policyholders' lapsation behavior in Malaysia. *Journal of Asian Finance, Economics and Business*, *8*(4), 89–97. https://doi.org/10.13106/jafeb.2021.vol8.no4.0089

Kassim, S., Abd Hamid, M. A., & Daud, N. M. (2019). Policy lapsation in life insurance: An exploratory study of causes and consequences. *International Journal of Economics, Management and Accounting*, *27*(2), 175–192.

Kaur, M., & Singh, B. (2020). Financial literacy and awareness of life insurance among university students. *International Journal of Financial Services Management*, *10*(1), 25–39. https://doi.org/10.1504/IJFSM.2020.105763

Khan, M. T. I., Islam, M. A., & Abedin, M. Z. (2022). Role of insurance literacy on insurance adoption: Evidence from a developing country. *Asian Journal of Economics and Banking*, *6*(1), 40–55. https://doi.org/10.1108/AJEB-04-2021-0048

Lee, M., & Chen-Yu, H. (2021). The role of perceived value in predicting repurchase intention in life insurance services. *Journal of Financial Services Marketing*, *26*(2), 41–52. https://doi.org/10.1057/s41264-020-00085-7

Li, D., & Moshirian, F. (2021). Financial literacy and trust in financial institutions. *Journal of Financial Services Research*, *60*(2), 237–260. https://doi.org/10.1007/s10693-021-00342-w

Life Insurance Association of Malaysia. (2020). *Annual report 2020*. https://www.liam.org.my/flip/2020/mobile/index.html

Lin, X., Zhang, Y., & Song, F. (2017). Does financial literacy affect individuals' insurance decisions? *China Economic Review*, *45*, 84–98. https://doi.org/10.1016/j.chieco.2017.05.003

Lusardi, A., & Mitchell, O. S. (2014). The economic importance of financial literacy: Theory and evidence. *Journal of Economic Literature*, *52*(1), 5–44. https://doi.org/10.1257/jel.52.1.5

Mahdzan, N. S., & Tabiani, S. (2013). The impact of financial literacy on individual saving: An exploratory study in the Malaysian context. *Transformations in Business & Economics*, *12*(1), 41–55.

Malaysian Communications and Multimedia Commission. (2020). *Internet users survey 2020*. https://www.mcmc.gov.my/en/resources/statistics/internet-users-survey

Milhaud, X., Loisel, S., & Maume-Deschamps, V. (2011). Surrender triggers in life insurance: What main features affect the surrender behavior in a classical economic context? *Bulletin Français d'Actuariat*, *11*(22), 5–48.

Nguyen, T. D., Nguyen, T. M., Nguyen, V. K., & Pham, L. T. M. (2020). Trust and customer satisfaction: A mediation model for repurchase intention in life insurance. *Journal of Asian Finance, Economics and Business*, *7*(3), 321–327. https://doi.org/10.13106/jafeb.2020.vol7.no3.321

Nor, F. M., Rahim, F. A., & Ismail, N. (2020). Socioeconomic factors influencing life insurance ownership: Evidence from Malaysia. *Journal of Management and Marketing Review*, *5*(3), 203–213. https://doi.org/10.35609/jmmr.2020.5.3(6

Organisation for Economic Co-operation and Development. (2017). *G20/OECD INFE report on consumer protection in insurance*. https://www.oecd.org/finance/G20-OECD-INFE-report-consumer-protection-insurance.pdf

Organisation for Economic Co-operation and Development. (2021). *Advancing the measurement of insurance literacy*. https://www.oecd.org/finance/Advancing-measurement-insurance-literacy.pdf

Rahim, H. L., Naim, D. M., & Yusof, Z. M. (2019). Factors influencing intention to purchase life insurance: A case study in Malaysia. *International Journal of Academic Research in Business and Social Sciences*, *9*(6), 56–69. https://doi.org/10.6007/IJARBSS/v9-i6/5931

Sanjeewa, W. S., Ouyang, H., Gao, Y., & Liu, Y. (2019). Decision making in personal insurance: Impact of insurance literacy. *Sustainability*, *11*(23), Article 6795. https://doi.org/10.3390/su11236795

Shamsuddin, S. N., Ismail, N., & Roslan, N. F. (2024). Development of insurance literacy construct in modeling life insurance ownership and lapse determinants: A descriptive analysis. *AIP Conference Proceedings*, *3150*(1), Article 060001. https://doi.org/10.1063/5.0216142

Sinha, A., Jaiswal, R., Pal, B. D., Shukla, K., Sundar, R., Natesh, G., & Singh, S. (2011). *Pre-launch survey report of insurance awareness campaign* [Unpublished report]. Insurance Regulatory and Development Authority of India.

Subashini, S., & Velmurugan, R. (2015). Lapsation in life insurance policies. *International Journal of Advance Research in Computer Science and Management Studies*, *3*(4), 41–45.

Swiss Re Institute. (2022). *World insurance: Inflation risks front and centre* (Sigma Report No. 4/2022). https://www.swissre.com/institute

Tan, L. K., & Lee, M. (2019). Financial literacy and insurance awareness in Malaysia: A review. *International Journal of Business and Society*, *20*(1), 1–18.

Tennyson, S. (2011). Consumers' insurance literacy: Evidence from survey data. *Financial Services Review*, *20*(3), 165–179.

Yaacob, H., & Jaafar, N. M. (2017). Determinants of life insurance demand among Muslim consumers in Malaysia. *Journal of Islamic Economics, Banking and Finance*, *13*(1), 134–153. https://doi.org/10.12816/0045662