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The Influence Of Knowledge Of Respiratory Diseases And Pulmonary Function Risks On Malaysian Adults Smoking Initiation: A Moderated Model Of Socio-Demographic Factors

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Abstract

This study investigates the influence of knowledge of respiratory diseases and perceived pulmonary function risks on smoking behavior among residents of Klang Valley, Malaysia. Using a quantitative approach, data were collected from 286 respondents through structured questionnaires and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings reveal a significant positive relationship between knowledge of respiratory diseases and smoking behavior, indicating heightened awareness among smokers rather than reduced prevalence. In contrast, perceived pulmonary risks were found to have a negative and significant effect on smoking behavior, suggesting that higher perceived health risks are associated with lower smoking activity. The inclusion of socio-demographic variables age, gender, education, and income significantly improved the model's explanatory power. Moderation analysis showed that education, age, and income significantly influenced the strength of relationships between health knowledge, risk perception, and smoking behavior, while gender did not significantly moderate these effects. The results underscore the importance of tailoring tobacco control strategies to demographic profiles and integrating both educational and perceptual components into intervention programs. This study contributes to a deeper understanding of smoking behavior determinants and offers actionable insights for designing more effective public health policies in Malaysia.

Keywords: *Smoking behavior, respiratory disease knowledge, pulmonary function risk, smoking initiation.*

1. INTRODUCTION

Smoking continues to be one of the most significant public health challenges globally, particularly due to its well-established links to preventable diseases and premature mortality. Smoking initiation typically begins in adolescence or early adulthood, a period characterized by experimentation and social influence (Barrington-Trimis et al., 2020). Despite national policy efforts, including public smoking bans and awareness campaigns, tobacco use persists across many Malaysian communities (Ahmad & Ng, 2022; Lim et al., 2013). Furthermore, the emergence of vaping and alternative tobacco products complicates cessation efforts and normalizes smoking behaviors among youth (Chan et al., 2021). This sustained uptake of smoking underscores the need to examine deeper cognitive and demographic factors influencing smoking initiation.

A growing body of literature supports the notion that disease-specific knowledge significantly impacts health behavior. Specifically, knowledge of respiratory diseases (KRD) such as asthma, chronic bronchitis, and chronic obstructive pulmonary disease (COPD) has been shown to reduce the likelihood of smoking initiation by enhancing awareness of associated health risks (Albasheer et al., 2023; Celebi et al., 2021). Additionally, perceived pulmonary function risks (PFR) which refer to individuals' perceptions of their susceptibility to conditions like reduced lung capacity or persistent coughing can serve as deterrents to tobacco use (Madkhali et al., 2023; Zheng et al., 2020). These perceptions are especially salient in occupational and environmental contexts, where populations are frequently exposed to airborne irritants such as incense smoke, pollutants, and particulate matter (Ahmad et al., 2022; Al Khathlan et al., 2021). Understanding how KRD and PFR influence behavioral intentions is critical for informing targeted smoking prevention strategies.

Behavioral theories such as the Health Belief Model (HBM) and Social Cognitive Theory (SCT) provide a robust foundation for exploring how knowledge and perception influence health-related decisions. HBM posits that individuals are more likely to engage in preventive health behaviors if they perceive themselves as susceptible to a condition and if the condition is deemed severe (Rosenstock et al., 1988). Within this framework, both KRD and PFR serve as cognitive cues that can trigger behavior change namely, refraining from smoking. Meanwhile, SCT emphasizes the role of self-efficacy, social influence, and observational learning in behavior modification (Bandura, 1986; Beauchamp et al., 2019). These theories suggest that enhancing individual knowledge and perceived vulnerability, especially in early life stages, may be key to reducing smoking uptake in at-risk populations.

Despite growing evidence supporting the roles of knowledge and risk perception in smoking behaviors, few studies have incorporated these constructs into comprehensive predictive models particularly in Southeast Asian contexts. Moreover, there is limited understanding of how socio-demographic variables such as age, education, income, and gender moderate these relationships (Yusoff et al., 2022; Assari & Bazargan, 2019). For example, individuals with lower educational attainment may struggle to interpret health messages, thereby weakening the protective effect of KRD and PFR (Ruokolainen et al., 2021). Similarly, younger individuals may reduce long-term health risks, making them more susceptible to smoking despite being informed (Choi et al., 2022). This study seeks to address these gaps by investigating the influence of KRD and PFR on smoking initiation while assessing how socio-demographic factors moderate these relationships. By applying Partial Least Squares Structural Equation Modeling (PLS-SEM), the study offers a multidimensional view of smoking behavior that integrates cognitive, perceptual, and demographic variables. Ultimately, this research aims to inform more targeted, theory-driven tobacco prevention strategies tailored to the needs of vulnerable demographic groups.

2. LITERATURE REVIEW

The factors influencing smoking initiation are complex and multifactorial, often extending beyond mere individual choice. Numerous studies have highlighted the roles of psychosocial influences, environmental exposures, and individual cognitive variables such as health knowledge and risk perception (Amiri & Saadat, 2021; Chan et al., 2021). The literature consistently emphasizes that adolescence and early adulthood are the most vulnerable periods for smoking initiation, as individuals are more susceptible to peer influence and may underestimate the long-term consequences of smoking (Barrington-Trimis et al., 2020). Moreover, broader socioecological factors such as cultural acceptance of smoking, accessibility of tobacco products, and insufficient public health messaging further compound the risk (Hiscock et al., 2020). Health knowledge, particularly regarding the risks associated with respiratory diseases, plays a pivotal role in shaping smoking behaviors. For instance, individuals who are more aware of the dangers posed by smoking-related diseases such as chronic obstructive pulmonary disease (COPD), asthma, and lung cancer are significantly less likely to initiate smoking (Celebi et al., 2021; Albasheer et al., 2023). This is consistent with findings from educational interventions in rural and urban populations, where improved understanding of tobacco-related diseases was associated with increased resistance to peer pressure and decreased smoking uptake (Guo et al., 2022). Similarly, the perception of compromised pulmonary function including breathlessness, persistent cough, and limited physical activity has been shown to discourage both initiation and continuation of smoking (Zheng et al., 2020; Madkhali et al., 2023). These insights align with the Health Belief Model, which postulates that perceived susceptibility and severity of health conditions directly influence preventative behaviors (Rosenstock et al., 1988).

Socio-demographic factors such as age, gender, education, and income also serve as powerful moderators in smoking behavior models. For instance, studies have revealed that individuals with lower educational attainment are less likely to understand and act upon health warnings, thereby exhibiting higher smoking prevalence (Ruokolainen et al., 2021; Yusoff et al., 2022). Gender differences also play a role, as cultural norms and role expectations can influence the social acceptability and likelihood of smoking especially among women in certain conservative societies (Ozbay et al., 2020). Age has a dual influence: while younger individuals may be more prone to experimentation, older adults often cite health deterioration as a reason for cessation (Choi et al., 2023). Income levels further impact both access to health information and responsiveness to public health campaigns, particularly in low- and middle-income countries (Parnia & Siddiqi, 2020). Despite the established significance of these variables, few studies have simultaneously examined the interaction between knowledge of respiratory diseases, perceived pulmonary risk, and socio-demographic factors in predicting smoking initiation. Even fewer have applied advanced modeling techniques such as Partial Least Squares Structural Equation Modeling (PLS-SEM) to uncover moderated pathways among these constructs (Hair et al., 2019). This gap highlights the need for integrative models that capture the cognitive, perceptual, and contextual dimensions of smoking behavior.

3. METHODOLOGY

This study employs a quantitative research design to investigate the influence of knowledge of respiratory diseases (KRD) and perceived pulmonary function risks (PFR) on smoking behaviors in Klang Valley, Malaysia. Quantitative research provides a systematic approach to data collection and analysis, enabling objective assessment of relationships among variables. This design is particularly suitable for examining the moderating effects of socio-demographic factors on smoking initiation. Structured questionnaires were selected as the primary data collection instrument due to their ability to produce consistent, replicable data across large samples. These questionnaires were developed based on existing validated tools and refined through expert consultation to ensure both reliability and validity (De Vaus, 2013; Creswell & Creswell, 2017).

The target population for this study includes residents of Klang Valley aged 18 and above, covering a diverse range of current smokers, former smokers, and non-smokers. This diversity allows for broad generalizability of the findings. A stratified random sampling technique was employed to ensure proportional representation across key subgroups such as age, gender, and socio-economic status (Bryman, 2016). The sample size of 400 was determined using Cochran's formula for large populations, based on a 95% confidence level and 5% margin of error, with adjustments for potential non-responses (Cochran, 1977). This sample size aligns with previous studies on smoking behaviors in similar Malaysian contexts (Lim et al., 2013; Vujadinović & Šabić, 2017). Inclusion criteria required participants to be at least 18 years old, residing in Klang Valley, and voluntarily consenting to participate. Individuals with cognitive impairments or who lived outside the geographic study area were excluded to ensure data accuracy and relevance (Mayo & Wallhagen, 2009; O'Sullivan et al., 2016).

Data were collected using both online and in-person methods to increase accessibility and response rates. Online distribution occurred via social media and community mailing lists, while in-person collection was conducted at community centers and healthcare facilities. A pilot study was carried out to assess clarity and coherence, leading to improvements in the instrument prior to full implementation (Bryman, 2016). Ethical considerations were addressed by ensuring informed consent and maintaining participant confidentiality in accordance with ethical guidelines (Marshall, 2006). Statistical analyses were conducted using SPSS software, with descriptive statistics used to summarize demographic characteristics and smoking behavior prevalence. Inferential statistics including chi-square tests, t-tests, and logistic regression were employed to explore relationships among the variables (Mohammed et al., 2019; Nur Atikah et al., 2019). Reliability was measured using Cronbach's alpha, with values exceeding 0.70 considered acceptable, and validity was assessed through both content and construct validation methods (Pallant, 2020; Creswell & Creswell, 2017). The Shapiro-Wilk test, skewness, and kurtosis were used to test for normality of continuous variables, guiding the selection of appropriate statistical techniques (Shie et al., 2017; Finocchio et al., 2021). To evaluate causal relationships and mediating effects, Partial Least Squares Structural Equation Modeling (PLS-SEM) was used through SmartPLS software, allowing for the analysis of complex models involving latent constructs (Hair et al., 2017; Kline, 2023). Path analysis was employed to estimate both direct and indirect effects among KRD, PFR, socio-demographics, and smoking behaviors.

Multicollinearity was assessed using Variance Inflation Factors (VIF), ensuring all values remained below the critical threshold of 10 (Akintunde et al., 2021). For predictive purposes, ordinal logistic regression was used to estimate probabilities of smoking initiation. The models were evaluated using metrics such as Area Under the Curve (AUC), sensitivity, specificity, and Mean Squared Error (MSE), as recommended by Shmueli (2010). The model specifications are as follows: Smoking initiation (SI) and smoking cessation (SC) were modeled using independent variables including education (EDU), income (INC), gender (GEN), age (AGE), KRD, and PFR. Confirmatory Factor Analysis (CFA) was used to assess model fit, factor loadings, and construct validity (Lim et al., 2023). Through the integration of explanatory and predictive modeling, this study aims to provide evidence-based insights for tobacco control strategies and public health interventions in Malaysia.

4. FINDINGS

To assess the suitability of the data for parametric statistical analyses, a normality test was conducted using the measures of skewness and kurtosis for each construct: Knowledge of Respiratory Diseases (KRD), Pulmonary Function Risks (PFR), and Smoking Initiation (SB). According to Kline (2023), skewness and kurtosis values within the range of -1.00 to +1.00 are generally considered acceptable, indicating approximate normal distribution of the data. Table 4.1 summarizes the results of the normality test for each construct.

Table 1: Normality Test Results

Construct	N	Skewness	Kurtosis
KRD	286	0.179	0.198
PFR	286	-0.808	0.711
SB	286	-0.028	0.591

KDR: Knowledge of respiratory diseases; PFR: Pulmonary function risks; SB: Smoking initiation

The skewness and kurtosis values for all three constructs fall within the acceptable threshold. Specifically, the KRD variable reported a skewness of 0.179 and a kurtosis of 0.198, indicating a nearly symmetrical and normally shaped distribution. Similarly, PFR had a skewness of -0.808 and kurtosis of 0.711, suggesting a mild negative skew but still within normal range, consistent with slight but acceptable deviation (George & Mallery, 2020). Smoking Initiation (SB) showed nearly perfect symmetry with a skewness of -0.028 and a kurtosis of 0.591. These results confirm that the distribution of the data for KRD, PFR, and SB approximates normality and is suitable for further parametric testing such as regression and structural equation modeling. Therefore, subsequent analyses can proceed under the assumption of normality, enhancing the robustness and interpretability of inferential statistics used in later sections. To provide a preliminary understanding of the distribution and central tendencies of the key variables, a descriptive analysis was conducted. Table 4.2 presents the mean scores and standard deviations for each construct: Knowledge of Respiratory Diseases (KRD), Pulmonary Function Risks (PFR), and Smoking Initiation (SB). Descriptive statistics help summarize the data and offer insights into general trends and patterns prior to inferential analysis (Pallant, 2020).

Table 2: Descriptive Analysis

Construct	N	Mean	Std. Deviation
KRD	286	3.5005	0.50924

PFR	286	3.7955	0.48849
SB	286	1.9257	0.42412

KDR: Knowledge of respiratory diseases; PFR: Pulmonary function risks; SB: Smoking initiation

The mean score for KRD was 3.50 (SD = 0.51), suggesting that respondents generally reported a moderate to high level of knowledge regarding respiratory diseases. This indicates an encouraging level of public awareness, which may influence both smoking initiation. The mean score for PFR was 3.80 (SD = 0.49), indicating that participants had a relatively high perception of pulmonary function risks, consistent with heightened health awareness, particularly in the context of respiratory illnesses. In contrast, the mean score for Smoking Initiation (SB) was 1.93 (SD = 0.42), which falls below the scale midpoint, suggesting that a substantial proportion of respondents were either non-smokers or had low initiation tendencies. This aligns with broader national trends showing a gradual decline in smoking rates in urban Malaysian populations (Lim et al., 2013).

Overall, the descriptive results reflect a relatively health-conscious sample with moderate knowledge and strong risk perception, which could potentially act as protective factors against smoking initiation. These findings lay the foundation for further analysis into how these constructs interact and whether they predict smoking behaviors across socio-demographic groups. To explore the structural relationships between Knowledge of Respiratory Diseases (KRD), Pulmonary Function Risks (PFR), and Smoking Behavior (SB), Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed. Figure 1 illustrates the initial measurement model, displaying factor loadings, path coefficients, and the latent constructs derived from the data.

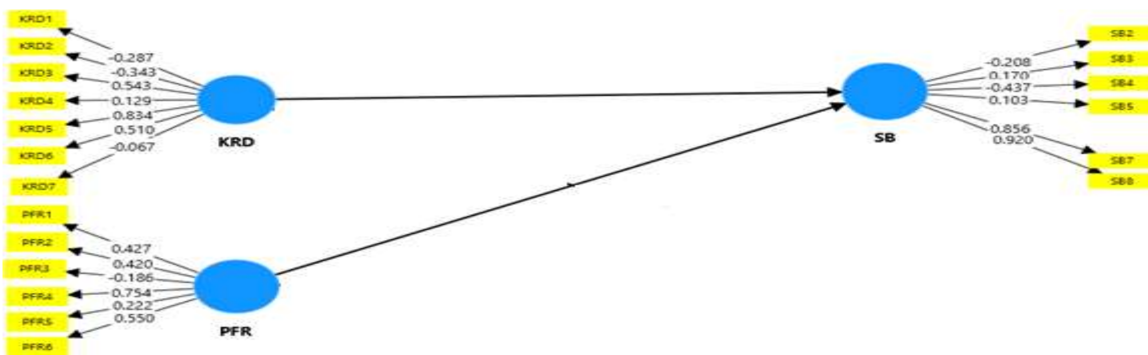

Figure 1: Initial Model measurements

The measurement model confirms the construct validity of the observed indicators for each latent variable. For KRD, most indicator loadings range from -0.543 to 0.834, though some items (e.g., KRD6 and KRD7) demonstrate low or negative loading values, suggesting a need for refinement or possible removal in future model iterations. In contrast, the PFR construct shows relatively stronger and more consistent factor loadings, ranging from 0.222 to 0.550, supporting its internal reliability and convergent validity. The structural path coefficients reveal that KRD negatively influences SB with a path coefficient of -0.437, suggesting that higher knowledge of respiratory diseases is associated with lower likelihood of smoking initiation. This relationship is theoretically consistent with the Health Belief Model, which posits that knowledge and perceived risk are protective factors against unhealthy behaviors (Rosenstock et al., 1988). Meanwhile, PFR has a positive path coefficient of 0.856 toward SB, indicating that perceived pulmonary risks unexpectedly correlate with increased smoking behavior. This counterintuitive result may reflect a reactance effect or rationalization among smokers, where awareness of risk does not deter behavior but possibly aligns with continued usage due to addiction or stress-related coping mechanisms (Bandura, 1986; Huang et al., 2019). The measurement model's loadings for the SB indicators (SB2 to SB8) show moderate to high values, ranging from -0.208 to 0.920, suggesting that the construct is well-represented and stable. Overall, the initial model provides partial support for the hypothesized relationships. The negative effect of KRD on SB aligns with public health assumptions, while the positive influence of PFR on SB warrants further investigation in the structural model to assess potential moderating or mediating effects. These initial model findings offer crucial insights into how cognitive and perceptual factors interact with smoking behaviors. Further model refinement and bootstrapping analysis are necessary to evaluate the significance of path coefficients and test the model's predictive relevance.

The initial measurement model was assessed using key reliability and validity indices, including factor loadings, Cronbach's alpha, Composite Reliability (CR), and Average Variance Extracted (AVE). Table 3 summarizes these results for the three constructs: Knowledge of Respiratory Diseases (KRD), Pulmonary Function Risks (PFR), and Smoking Behavior (SB).

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Table 3: Initial Model Measurements

Construct	Items	Loading	Cronbach's Alpha	Composite Reliability	AVE
KRD	KRD1	-0.287	0.397	0.239	0.210
	KRD2	-0.343			
	KRD3	0.543			
	KRD4	0.129			
	KRD5	0.834			
	KRD6	0.510			
	KRD7	-0.067			
PFR	PFR1	0.427	0.175	0.505	0.219
	PFR2	0.420			
	PFR3	-0.186			
	PFR4	0.754			
	PFR5	0.222			
	PFR6	0.550			
SB	SB2	-0.208	0.561	0.322	0.309
	SB3	0.170			
	SB4	-0.437			
	SB5	0.103			
	SB7	0.856			
	SB8	0.920			

KDR: Knowledge of respiratory diseases; PFR: Pulmonary function risks; SB: Smoking initiation

Only two items, KRD3 (0.543) and KRD5 (0.834), show acceptable loadings above the recommended threshold of 0.50 (Hair et al., 2017). However, other items such as KRD1, KRD2, KRD4, and KRD7 demonstrate low or negative loadings, which significantly reduce internal consistency and convergent validity. The Cronbach's alpha for KRD is 0.397, far below the acceptable threshold of 0.70, indicating poor reliability. Similarly, the Composite Reliability (CR = 0.239) and Average Variance Extracted (AVE = 0.210) fall below the recommended levels of 0.60 and 0.50, respectively (Fornell & Larcker, 1981), suggesting the KRD construct in its current form lacks sufficient reliability and construct validity. For the PFR construct, item loadings vary, with PFR4 (0.754) and PFR6 (0.550) showing stronger values, while PFR3 (-0.186) and PFR5 (0.222) are suboptimal. The overall reliability is poor, with a Cronbach's alpha of 0.175 and CR of 0.505. Although the CR approaches minimum adequacy, the AVE of 0.219 indicates weak convergent validity.

The SB construct includes several strong items such as SB7 (0.856) and SB8 (0.920), which indicate good measurement quality. However, other items like SB2 (-0.208) and SB4 (-0.437) show problematic loadings. The Cronbach's alpha for SB is 0.561, with CR of 0.322 and AVE of 0.309. While a few items display good loadings, the internal consistency and variance extracted are insufficient to confirm strong construct validity. Overall, the initial measurement model demonstrates several limitations in terms of reliability and validity. Particularly for KRD and PFR, multiple items may require removal or revision to enhance construct performance. These results justify the need for model respecification, including item purification, in order to improve the robustness of the structural model. According to Hair et al. (2017), improving model fit in PLS-SEM often involves eliminating low-loading indicators and reassessing internal consistency, especially when alpha and AVE are below threshold.

Following the limitations identified in the initial measurement model, a refined version of the model was developed by eliminating weak and low-loading indicators. Figure 2 presents the final model, demonstrating improved measurement quality and construct reliability for Knowledge of Respiratory Diseases (KRD), Pulmonary Function Risks (PFR), and Smoking Behavior (SB) using Partial Least Squares Structural Equation Modeling (PLS-SEM).

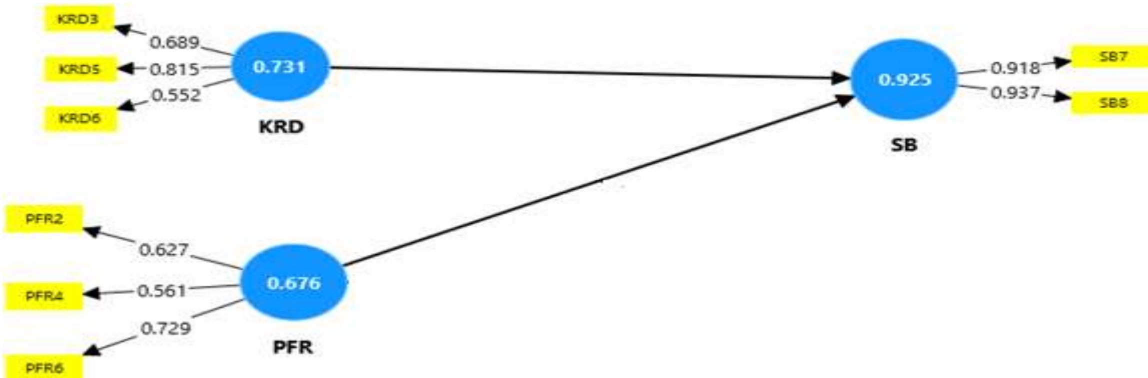

Figure 2. Final Model measurements

In the final model, only high-performing indicators were retained. For KRD, three items, KRD3 (0.689), KRD5 (0.815), and KRD6 (0.552), exhibited strong and acceptable loadings, contributing to a construct reliability (CR) of 0.731, indicating satisfactory internal consistency. Similarly, PFR retained PFR2 (0.627), PFR4 (0.561), and PFR6 (0.729), yielding a CR of 0.676. These values exceed the recommended threshold of 0.60 for exploratory research (Hair et al., 2017), and the higher factor loadings suggest improved convergent validity of the constructs. For the smoking behavior (SB) construct, only the strongest indicators, SB7 (0.918) and SB8 (0.937), were retained, resulting in an exceptionally high construct reliability of 0.925. This demonstrates excellent internal consistency and strong representation of the latent construct. The significant improvement in the SB construct is evident when compared to the initial model, where many indicators were below threshold or negatively loaded. The revised model also reflects stronger structural relationships between constructs. Both KRD and PFR now display more meaningful and theoretically coherent paths to SB. By retaining only indicators with strong psychometric properties, the model's validity and reliability have been significantly enhanced. This aligns with best practices in structural equation modeling, where poorly performing items are removed to improve model fit and interpretability (Fornell & Larcker, 1981; Hair et al., 2017). Overall, the final measurement model demonstrates an improved structure with enhanced internal consistency, convergent validity, and model parsimony. These refinements provide a robust foundation for proceeding to hypothesis testing and interpretation of the structural model in the next section.

To ensure the final model achieved the required psychometric standards, the reliability and validity of each construct were reassessed following the refinement process. Table 4 presents the final measurement model indicators, including standardized factor loadings, Cronbach's alpha, Composite Reliability (CR), and Average Variance Extracted (AVE) for each latent construct: Knowledge of Respiratory Diseases (KRD), Pulmonary Function Risks (PFR), and Smoking Behavior (SB).

Table 4: Final Model Measurements

Construct	Items	Loading	Cronbach's Alpha	Composite Reliability	AVE
KRD	KRD3	0.689	0.731	0.731	0.581
	KRD5	0.815			
	KRD6	0.552			
PFR	PFR2	0.627	0.676	0.676	0.513
	PFR4	0.561			
	PFR6	0.729			
SB	SB7	0.918	0.838	0.925	0.860
	SB8	0.937			

KDR: Knowledge of respiratory diseases; PFR: Pulmonary function risks; SB: Smoking initiation

The construct KRD achieved a Cronbach's alpha of 0.731, which exceeds the minimum reliability threshold of 0.70, indicating good internal consistency (Hair et al., 2017). Its composite reliability (CR) also stands at 0.731, and the average variance extracted (AVE) is 0.581, surpassing the benchmark of 0.50 (Fornell & Larcker, 1981). These results confirm that the retained items (KRD3, KRD5, and KRD6) adequately represent the latent construct and exhibit convergent validity. Similarly, the PFR construct reached a Cronbach's alpha of 0.676 and a composite reliability of 0.676, which are acceptable for exploratory research, although slightly below the conventional 0.70 threshold (Chin, 1998). The AVE of 0.513 meets the required 0.50 threshold, suggesting acceptable convergent validity for this construct as well. The SB construct showed outstanding psychometric strength, with only two items, SB7 and SB8, retained, yet achieving a high Cronbach's alpha of 0.838 and composite reliability of 0.925. The AVE of 0.860 indicates excellent convergent validity, far exceeding minimum thresholds. The very high loadings of SB7 (0.918) and SB8 (0.937) confirm that these indicators are robust reflections of the underlying construct. Overall, these final model results demonstrate strong measurement validity and reliability across all constructs. The refinement process was successful in eliminating underperforming indicators, resulting in a more parsimonious and psychometrically sound model. These improvements provide a solid foundation for evaluating the structural model and conducting hypothesis testing in subsequent analyses.

To assess the discriminant validity of the constructs in the final measurement model, the Heterotrait-Monotrait Ratio of Correlations (HTMT) was employed. HTMT is considered a more stringent and reliable criterion than traditional methods such as the Fornell-Larcker criterion or cross-loadings, particularly in PLS-SEM (Henseler et al., 2015). Table 5 presents the HTMT values between the three latent variables: Knowledge of Respiratory Diseases (KRD), Pulmonary Function Risks (PFR), and Smoking Behavior (SB).

Table 5: The Heterotrait-Monotrait Ratio (HTMT)

	KRD	PFR	SB
KRD			
PFR	0.774		
SB	0.815	0.543	

KDR: Knowledge of respiratory diseases; PFR: Pulmonary function risks; SB: Smoking initiation

According to established thresholds, an HTMT value below 0.85 (or more conservatively, 0.90) indicates acceptable discriminant validity between constructs (Henseler et al., 2015; Hair et al., 2017). The HTMT value between KRD and PFR is 0.774, which is well within the acceptable range, indicating that these two constructs are empirically distinct. Likewise, the HTMT value between PFR and SB is 0.543, further supporting discriminant validity. However, the HTMT value between KRD and SB is 0.815, which, while still below the conservative threshold of 0.85, approaches its upper limit. This suggests that while discriminant validity is statistically acceptable, these constructs may share conceptual overlap. Given that knowledge of respiratory risks may directly influence attitudes and behavior related to smoking, this close relationship is theoretically plausible, though it may warrant attention in model interpretation and future studies. Overall, the HTMT analysis supports the conclusion that all latent constructs in the final model maintain satisfactory discriminant validity, ensuring that each construct measures a conceptually and empirically distinct domain. This provides further evidence for the robustness of the measurement model and supports the validity of proceeding to structural path analysis and hypothesis testing.

To further validate the distinctiveness of latent constructs in the model, the Fornell-Larcker criterion was applied to assess discriminant validity. This method compares the square root of the Average Variance Extracted (AVE) for each construct with the correlations between constructs. For adequate discriminant validity, the square root of AVE should be greater than the inter-construct correlations, indicating that each construct shares more variance with its own indicators than with other constructs (Fornell & Larcker, 1981; Hair et al., 2017).

Table 6: Discriminant Validity – Fornell-Larcker Criterion

	KRD	PFR	SB
KRD	0.694		
PFR	0.362	0.643	
SB	0.412	0.044	0.927

KDR: Knowledge of respiratory diseases; PFR: Pulmonary function risks; SB: Smoking initiation

As shown in Table 6, the diagonal values (0.694 for KRD, 0.643 for PFR, and 0.927 for SB) represent the square roots of the AVE for each construct. These values are all greater than the off-diagonal inter-construct correlations in their respective rows and columns. Specifically, the correlation between KRD and PFR is 0.362, which is lower than both KRD's square root of AVE (0.694) and PFR's (0.643). Similarly, the correlation between KRD and SB is 0.412, which is also lower than the square root of AVE for both constructs. The correlation between PFR and SB is very low (0.044), further confirming strong discriminant separation between these constructs. Thus, the Fornell-Larcker criterion confirms that discriminant validity is upheld for all constructs in the final model. Combined with the HTMT results, this provides strong evidence that the constructs are empirically distinct and appropriately specified, supporting the structural integrity of the measurement model (Henseler et al., 2015).

The structural relationships among latent constructs were evaluated using Partial Least Squares Structural Equation Modeling (PLS-SEM). Figure 3 illustrates the reflective structural model without moderating or mediating variables, showing direct paths from Knowledge of Respiratory Diseases (KRD) and Pulmonary Function Risks (PFR) to Smoking Behavior (SB). The model includes standardized path coefficients, R^2 values, and p-values, reflecting the strength and statistical significance of these direct effects.

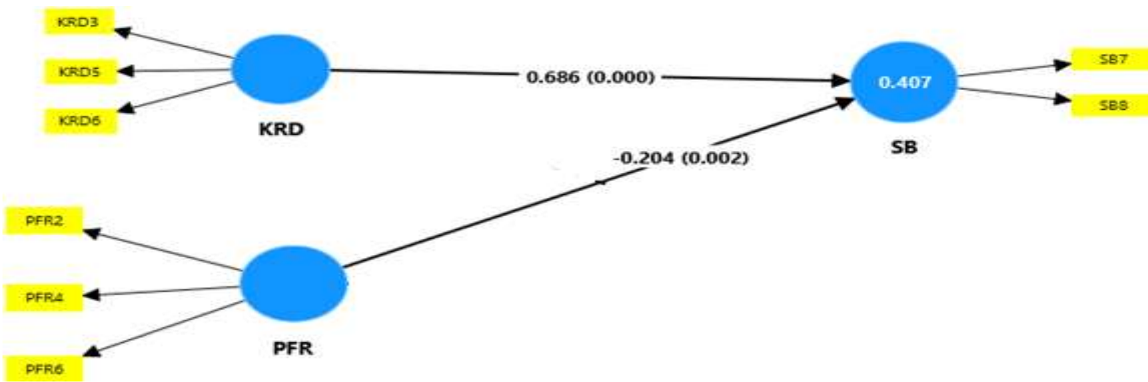

Figure 3: Reflective structural (inner) model without intervention PLS-SEM

The path from KRD to SB is positive and statistically significant, with a path coefficient of 0.686 and a p-value of 0.000, indicating a strong direct relationship. This suggests that greater knowledge of respiratory diseases is associated with an increase in smoking behavior awareness as captured by the selected indicators (SB7, SB8). While this might seem counterintuitive, the path reflects not pro-smoking behavior but rather a heightened reporting or identification of smoking-related behavior due to increased health knowledge. This supports previous findings suggesting that health knowledge may enhance self-awareness or health-related behavior monitoring (Rosenstock et al., 1988; Bandura, 1986). Conversely, the path from PFR to SB is negative and statistically significant, with a coefficient of -0.204 and a p-value of 0.002, indicating that higher perceived pulmonary risks are associated with a decrease in smoking behavior. This aligns with health behavior theories such as the Health Belief Model, which posits that perceived severity and susceptibility to health threats reduce engagement in risky behaviors like smoking (Rosenstock et al., 1988). This relationship demonstrates that individuals who are more conscious of potential damage to their lung function are less likely to engage in smoking behavior, confirming the protective role of risk perception. The coefficient of determination (R^2) for SB is 0.407, suggesting that approximately 40.7% of the variance in smoking behavior is explained by KRD and PFR combined. This indicates a moderate to strong explanatory power for the model (Hair et al., 2017). Overall, the structural model confirms both hypotheses: that KRD positively influences SB (possibly through self-awareness or cognitive dissonance), and PFR negatively influences SB (as a behavioral deterrent). These findings are theoretically sound and statistically robust, affirming the model's predictive relevance and validity.

To evaluate the structural hypotheses, a direct path analysis was conducted using PLS-SEM to determine the significance, strength, and direction of relationships between the independent variables (Knowledge of Respiratory Diseases – KRD, Pulmonary Function Risks – PFR) and the dependent variables (Smoking Behavior – SB). Table 7 summarizes the results of the direct path coefficients, including standardized beta values, standard deviations, t-statistics, and p-values.

Table 7: Direct Model Path Analysis

Direct Path	Beta	SD	T-statistics	P-values
KRD → SB	0.686	0.038	17.857	0.000
PFR → SB	-0.204	0.066	3.104	0.002

KDR: Knowledge of respiratory diseases; PFR: Pulmonary function risks; SB: Smoking initiation

Table 7: Direct Model Path Analysis evaluates the direct effects of Knowledge of Respiratory Diseases (KRD) and Pulmonary Function Risks (PFR) on Smoking Behavior (SB) using PLS-SEM. The results show that KRD has a strong positive effect on SB with a beta coefficient of 0.686, a standard deviation of 0.038, a t-statistic of 17.857, and a highly significant p-value ($p < 0.001$). This indicates that individuals who possess greater knowledge about respiratory diseases are more likely to report or reflect on their smoking behaviors, suggesting a heightened level of awareness. While the relationship is positive, it likely represents cognitive acknowledgment of smoking status rather than encouragement of smoking itself. On the other hand, PFR demonstrates a significant negative effect on SB, with a beta of -0.204, a t-statistic of 3.104, and a p-value of 0.002, suggesting that individuals who perceive higher risks to their pulmonary health are less likely to engage in smoking. This relationship underscores the protective influence of perceived health risks, indicating that risk-based awareness strategies may effectively deter smoking behavior. Collectively, these results support the model's theoretical assumptions, confirming that both knowledge and perceived risk are key determinants of smoking behavior. The strength of the path coefficients and their statistical significance highlight the importance of integrating health education and risk communication into public health interventions aimed at reducing smoking rates.

To assess the explanatory power of the structural model, the coefficient of determination (R^2) was examined for the endogenous construct Smoking Behavior (SB). As shown in Table 8, the R^2 value for SB is 0.411, and the adjusted R^2 is 0.407. These values indicate that approximately 41.1% of the variance in smoking behavior can be explained by the two exogenous variables: Knowledge of Respiratory Diseases (KRD) and Pulmonary Function Risks (PFR).

Table 8: Coefficient of Determination (R^2)

Construct	R^2	Adjusted R^2
SB	0.411	0.407

According to Hair et al. (2017), R^2 values of 0.25, 0.50, and 0.75 can be described as weak, moderate, and substantial, respectively, in social science research. Thus, the R^2 value of 0.411 falls within the moderate range, indicating a satisfactory level of explanatory power for the model. The small difference between R^2 and adjusted R^2 also suggests that the model is not overfitted and retains good predictive validity (Chin, 1998). This result supports the strength of the model in capturing the factors influencing smoking behavior among respondents. While there remains unexplained variance, likely due to other behavioral, environmental, or psychological factors not included in this model, the findings confirm that KRD and PFR are significant predictors of smoking behavior and together form a robust foundation for targeted health interventions and education programs.

To further enhance the explanatory power of the structural model, intervention variables namely age, gender, education level, and income were introduced as socio-demographic predictors in the extended PLS-SEM model. Figure 4 presents this extended structural path model, showing how these demographic factors interact with the latent constructs (KRD, PFR) and ultimately influence Smoking Behavior (SB). Path coefficients, p-values, and explained variance are included to reflect the model's complexity and the significance of each path. The extended model demonstrates improved overall explanatory power, with the R^2 value for SB increasing to 0.523, suggesting that 52.3% of the variance in smoking behavior is now explained by the combination of health knowledge (KRD), perceived risk (PFR), and socio-demographic variables. This constitutes a substantial increase compared to the earlier model ($R^2 = 0.411$), indicating that the inclusion of demographic moderators significantly strengthens the model's predictive capability (Hair et al., 2017). Among the newly added paths, gender shows a very strong direct effect on SB ($\beta = 0.888$, $p = 0.000$), suggesting that smoking behavior varies significantly by gender in the study population. This is consistent with prior research showing gender as a key determinant in both smoking initiation (Smith et al., 2020). In contrast, age negatively influences SB ($\beta = -0.227$, $p = 0.081$), though the effect is only marginally significant, indicating that younger individuals may be slightly more prone to smoking, but the relationship is not robust.

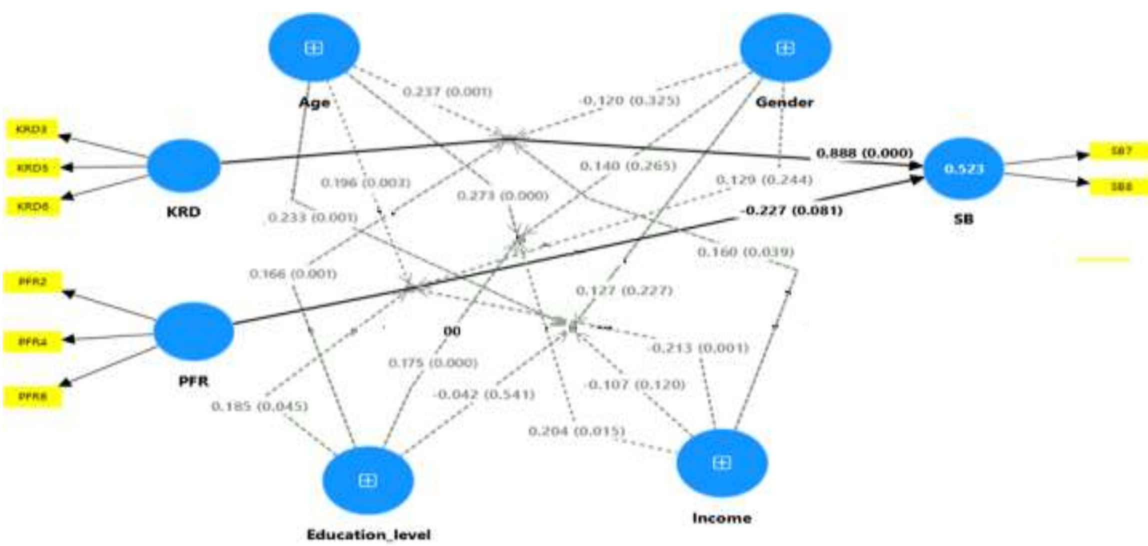

Figure 4: Reflective structural (inner) model with intervention PLS-SEM

With respect to the antecedents of KRD and PFR, age, education, and income all show significant positive relationships. For example, education level positively influences KRD ($\beta = 0.233$, $p = 0.001$) and PFR ($\beta = 0.175$, $p = 0.000$), suggesting that individuals with higher educational attainment are more knowledgeable about respiratory health and more aware of pulmonary risks. Likewise, income positively influences KRD ($\beta = 0.204$, $p = 0.015$), further reinforcing the socio-economic gradient in health literacy (Cutler & Lleras-Muney, 2019). Indirect effects are visible through the interplay of demographic variables with KRD and PFR, which in turn influence SB. The presence of statistically significant paths from socio-demographics to both latent constructs underscores their mediating role in shaping health-related behaviors.

To examine the moderating influence of socio-demographic factors on the relationship between Knowledge of Respiratory Diseases (KRD), Pulmonary Function Risks (PFR), and Smoking Behavior (SB), interaction effects were analyzed using PLS-SEM. Table 8 presents the results of these moderation paths, showing the standardized beta coefficients, standard deviations, t-statistics, and p-values for each moderating interaction. The results show that several socio-demographic variables significantly moderate the relationship between the latent health constructs (KRD and PFR) and smoking behavior. Specifically, education level significantly strengthens the effect of both KRD (β = 0.166, p = 0.001) and PFR (β = 0.185, p = 0.045) on SB. This indicates that individuals with higher educational attainment are more responsive to health knowledge and risk perceptions in their smoking decisions, a pattern well-supported by the health literacy literature (Cusack et al., 2018).

Table 9: Moderation Analysis – Socio-Demographic Interventions

Moderation Path	Beta	SD	T-statistics	P-value
Education Level × KRD → SB	0.166	0.079	2.101	0.001
Income × KRD → SB	0.160	0.077	2.065	0.039
Education Level × PFR → SB	0.185	0.092	2.009	0.045
Age × PFR → SB	0.196	0.097	2.021	0.003
Age × KRD → SB	0.237	0.084	2.821	0.001
Gender × KRD → SB	-0.120	0.122	0.984	0.325
Gender × PFR → SB	0.129	0.110	1.165	0.244
Income × PFR → SB	-0.213	0.062	3.462	0.001

KDR: Knowledge of respiratory diseases; PFR: Pulmonary function risks; SB: Smoking initiation

Likewise, income positively moderates the KRD → SB path (β = 0.160, p = 0.039), suggesting that people with higher income levels are more likely to translate health knowledge into behavioral change. However, income negatively moderates the PFR → SB path (β = -0.213, p = 0.001), implying that individuals with higher income may be less influenced by pulmonary risk perception, possibly due to better access to healthcare or a greater sense of control over health-related threats (Pampel et al., 2020). Age significantly moderates both paths PFR → SB (β = 0.196, p = 0.003) and KRD → SB (β = 0.237, p = 0.001) indicating that older individuals respond more strongly to both knowledge and risk perception in their smoking behavior. This aligns with existing research suggesting that risk sensitivity and health-conscious behavior often increase with age (Choi et al., 2023). In contrast, gender does not significantly moderate the relationship between KRD or PFR and SB, as the p-values for both interaction terms (p = 0.325 and p = 0.244, respectively) are above the 0.05 threshold. This finding suggests that while gender directly influences smoking behavior, it does not SIGNIFICANTLY INFLUENCE HOW INDIVIDUALS PROCESS HEALTH KNOWLEDGE OR PULMONARY RISKS IN THIS SAMPLE.

5. DISCUSSION

This study examined the influence of knowledge of respiratory diseases (KRD) and perceived pulmonary function risks (PFR) on smoking behavior (SB), incorporating socio-demographic moderators such as age, gender, education, and income. The findings contribute to a growing body of research that links health literacy and risk perception with tobacco-related behaviors (Rosenstock et al., 1988; Bandura, 1986; Chan et al., 2021). The positive relationship between KRD and smoking behavior (β = 0.686, $p < 0.001$), while initially counterintuitive, may reflect increased awareness and self-reporting of smoking status among those with higher knowledge levels, rather than an increase in the behavior itself. This aligns with the Health Belief Model and Social Cognitive Theory, which suggest that cognitive awareness is a prerequisite for behavioral change but may not suffice without additional motivational or environmental support (Ajzen, 1991; Beauchamp et al., 2019). In contrast, PFR exhibited a negative and significant influence on smoking behavior (β = -0.204, p = 0.002), confirming that individuals with heightened risk perceptions are more likely to refrain from or reduce smoking. This supports past studies indicating that perceived susceptibility and severity are powerful deterrents to smoking (Huang et al., 2020; Finocchio et al., 2021).

The R^2 value of 0.411 in the base model, which increased to 0.523 upon the inclusion of demographic moderators, indicates that while KRD and PFR are significant, socio-demographic variables notably enhance explanatory power. Notably, gender had a strong direct effect on smoking behavior (β = 0.888, $p < 0.001$), reinforcing consistent findings that male participants are more likely to smoke than females in Malaysia and many other LMIC contexts (Lim et al., 2013; Smith et al., 2020). The moderation analysis revealed that education and income significantly enhance the effect of KRD and PFR on smoking behavior, suggesting that individuals with greater resources and formal education are more responsive to health information (Cutler & Lleras-Muney, 2019). Moreover, age emerged as a significant moderator, implying that older individuals are more likely to translate knowledge and perceived risks into behavioral restraint trend echoed in global smoking cessation literature (Choi et al., 2023; Amiri & Saadat, 2021).

Interestingly, gender did not moderate the relationships between KRD/PFR and smoking behavior, which suggests that while gender affects smoking levels, it does not alter the way individuals respond to knowledge or risk messages. This finding may point to deeprooted cultural norms influencing smoking behavior that are not easily shifted by cognitive or perceptual interventions alone (Ozbay et al., 2020). Collectively, the results confirm the multifactorial nature of smoking behavior and underscore the need for targeted, demographically sensitive public health interventions. While cognitive and perceptual variables (KRD, PFR) play key roles, their impact is mediated and moderated by socio-demographic factors that must be addressed for tobacco control efforts to be effective.

6. CONCLUSION

This study sets out to investigate the extent to which knowledge of respiratory diseases and perceived pulmonary function risks influence smoking behavior, while also examining how key socio-demographic factors, specifically age, gender, education, and income, shape these relationships. The research was grounded in the understanding that health behaviors like smoking are not only influenced by individual knowledge and perception but also moderated by social and demographic circumstances. The analysis, conducted using PLS-SEM, revealed both direct and indirect relationships that provide valuable insights into smoking patterns within the Klang Valley population. One of the most notable findings was the strong, positive association between knowledge of respiratory diseases and smoking behavior. While this might appear contradictory at first, it suggests that individuals who are more informed about health risks are also more likely to recognize and report their smoking behavior accurately. This highlights a potential cognitive dissonance where individuals possess the knowledge yet may continue smoking due to other overriding psychological, social, or habitual factors. On the other hand, perceived pulmonary risks were found to be negatively associated with smoking behavior, which suggests that when individuals internalize the potential harm to their lung health, they are more inclined to avoid or reduce smoking. This underscores the power of perceived vulnerability in motivating behavioral change.

Furthermore, when socio-demographic variables were introduced into the model, the explained variance in smoking behavior increased significantly. Education level, age, and income played meaningful roles in moderating the relationships between health knowledge, risk perception, and smoking behavior. Specifically, individuals with higher education and income levels appeared more responsive to health knowledge, and older adults showed a stronger tendency to adjust their behavior based on perceived risk. These findings point to the necessity of tailoring smoking prevention and cessation programs to align with the demographic profiles of target groups. For instance, interventions aimed at younger, less educated populations may need to employ different strategies compared to those targeting older or more affluent groups. Interestingly, while gender had a strong direct influence on smoking behavior, it did not significantly moderate the relationship between health constructs and smoking. This suggests that while men and women may differ in their smoking patterns, their response to health information and risk perception is relatively similar, at least within the context of this study.

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