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# Path Analysis Using Structural Equation Modelling (SEM) to Examine the Moderation of Product Knowledge in the Effects of and Perceived Risk, Environmental Consciousness, and Subjective Norm on Purchase Intention

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**Abstract.** The objective of this research was to enhance the comprehension of consumer behaviour by exploring how purchase intentions are influenced by perceived risk, environmental consciousness, and subjective norms, which together create a complex interplay. SEM and PLS, focusing on the moderating role of product knowledge were employed in the study. While consumer marketing has well-established models, business marketing lacks similar references. This study contributes to the academic discourse and provides practical insights for organizations as they adapt to evolving customer preferences. The research technique included the evaluation of the measurement model via the use of reflective indicators, as well as the assessment of convergent and discriminant validity. Using bootstrapping, the structural model was then tested through the hypothesis testing, as well as the overall model quality and fit were evaluated using R square, Q square, F square, and SRMR. The results indicated that subjective norms played a more dominant role than perceived risk and environmental awareness in the context of purchase intention. However, the interaction between these factors and product knowledge did not significantly impact the purchase intention. The product knowledge is in-depth knowledge about the products marketed by a company. In this research, the product knowledge was a moderating variable, where the moderating variable could strengthen or weaken the independent variable. The R square value illustrated a high overall effect of exogenous/endogenous variables on purchase intention. The research contributes to the literature by bridging gaps in SEM application, shedding light on the complexities of consumer behaviour in business marketing, and advocating for a nuanced understanding of PLS-SEM's dual purpose. The findings offer valuable insights for researchers and practitioners in navigating the intricate landscape of consumer decision-making.

**Keywords:** Structural Equation Modelling, Path Analysis, Purchase Intention, Perceived Risk, Environmental Consciousness, Subjective Norm, Product Knowledge

## Introduction

In the research by Lashari et al. (2021) it was found that two variables did not have a statistically significant influence on the intention to purchase an electric vehicle: battery life; and non-monetary incentive policies. This shows that understanding the consumer behaviour towards purchasing electric vehicles is still a challenging and complex problem that requires further research. Therefore, researchers conducted investigations with the aim of expanding or finding out what factors influence EV purchase intentions.

The structural equation modelling (SEM) is a well-recognised and accepted technique in marketing research, as supported by the works of Hair et al. (2017) and Martínez-López et al. (2013). SEM is used to estimate complex models that include hidden chains of causation and interrelationships among theoretical entities. Composite-based partial least squares structural equation modelling (PLS-SEM) has significantly increased in popularity over the last twenty years for analysing marketing models (Sarstedt et al., 2022b). The previously mentioned topics also apply to several other business domains. The approach is frequently applied in these study domains to examine the origins of competitive advantage and success characteristics concerning pertinent goal constructs (Albers, 2010). Certain approach properties, such as PLS-SEM's ability to let searchers estimate highly complicated models with little sample requirements, are particularly highlighted by business marketing researchers (Yeniaras et al., 2020). The online surveys, in particular, can be beneficial when there is a small pool of potential respondents, like employees and managers, and a limited timeframe for recruitment in business marketing research.

Although PLS-SEM is being used by corporate marketing researchers more and more (see the review findings for articles in Industrial Marketing Management), several issues arise when applying the technology appropriately, including knowing when and where to utilize it. Covariance-based structural equation modelling (SEM) is a feasible substitute for partial least squares SEM (PLS-SEM) in SEM applications (Davvetas et al., 2020). The thorough and detailed explanations of the PLS-SEM approach have benefited researchers in corporate marketing (Chin, 1998; Henseler et al., 2012). Such explanations have facilitated their understanding of the technical distinctions among the SEM models. PLS-SEM primarily aims to make predictions due to its ability to decrease inexplicable variation in the dependent constructs of the structural model and the indicators of the measurement model (Sarstedt et al. 2022a). Covariance-based structural equation modelling (SEM) aims to anticipate and evaluate theories by generating a model-implied covariance matrix that closely resembles the observed covariance matrix. Partial least squares structural equation modelling (PLS-SEM) places equal importance on explanation and prediction.

In contrast, the covariance-based SEM gives more priority to explanation than prediction, as categorized by Gregor (2006). The dual emphasis of causal-predictive nature or the PLS-SEM's dual aim has been identified in pioneering research by Joreskog and Wold (1982). In addition to providing valuable information, these technical distinctions should be taken into account alongside other factors when choosing the most effective SEM approach for a specific research topic. However, applied business marketing researchers frequently don't seem to be aware of these factors. In corporate marketing research, there are no flagship PLS-SEM programs that researchers may turn to; in contrast to consumer marketing research, the American Customer Happiness Index (ACSI) model is a well-known tool that consumer marketing researchers (Guenther & Guenther, 2021) may use to assess the significance of the determinants of customer happiness and loyalty.

Amidst the ever-changing consumer behaviour, it has become crucial for both researchers and professionals to comprehend the complex connections between psychological factors and buying choices. This research endeavours to unravel the complex interplay of perceived risk, environmental consciousness, and subjective norm in shaping consumers' purchase intentions, with a nuanced exploration moderated by product knowledge. Employing the advanced analytical tools of Structural Equation Modelling (SEM) and specifically Partial Least Squares (PLS), this study aims to provide a comprehensive and robust examination of these variables. As contemporary consumers navigate a market saturated with diverse products and environmental considerations, an in-depth understanding of the moderating role of product knowledge is vital for tailoring marketing strategies and enhancing our grasp of the intricate pathways that influence purchase intentions. This study not only enhances the scholarly discussion on consumer behaviour but also provides valuable practical guidance for companies seeking to connect their products and services with the changing tastes and concerns of today's socially responsible customers.

The path analysis is an analysis developed by an applied geneticist Sewall Wright in 1934 that is used as a method to study determining the magnitude of influence among several variables, where some variables are seen as causes and other variables are considered as effects. This technique is also known as causing modelling. According to Li (1975), The cause-and-effect relationship between variables—often exogenous and endogenous—is the foundation of route analysis. When multiple regression analysis is not possible to analyse the link between complex variables (more than one endogenous variable), the route analysis is employed. The route analysis calculates the impact of various factors based on the route coefficient. One of the advantages of path analysis is that it can analyse the overall effect of an exogenous variable and break it down into direct and indirect effects.

Sewall Wright's concept was influenced by earlier formula discoveries, such as principal component analysis, which was discovered in 1901 by Karl Pearson, the creator of the Pearson correlation formula, and factor analysis, which was invented in 1904 by Charles Spearman, the creator of the Spearman correlation formula. These findings significantly impacted the advancement of structural equation modelling (SEM), founded on path analysis (PA), a concept often grouped with SEM by most individuals. The only fundamental commonality between PA and SEM is casualty. Later in its evolution, SEM represents a unidirectional and bidirectional/reciprocal/reciprocal causality model (officially termed non-recursive). In contrast, PA is more of a representation of a unidirectional causality model (technically called recursive). Wright's most significant contribution is his invention of the path coefficient approach within the framework of the causality connection, which serves as the foundation for relating causal difficulties to statistical problems. Inadvertently, this causes individuals to link causation with path analysis in later advancements. As for the link between route analysis and the causality model, there is no theoretical foundation for it, but there is a theory supporting the relationship between linear regression and the causality relationship. However, history indicates that route analysis and causation are related, according to Denis and Legerski (2006). Looking at historical circumstances, one can only support the relationship between route analysis and causation. In order to establish the connection between route analysis and causality models, it is important to provide a brief overview of Sewall Right's research in this area. His works have established a consensus on the relationship between these two concepts.

The validity test was carried out to determine whether the measuring instrument carried out its measuring function following the measurement objectives, ensuring that each item in the instrument could measure the research variable. The reliability test was carried out to determine the internal consistency of the indicator of a latent variable and the extent to which the indicator could identify a constructed variable (unobservable variable). The instrument is reliable if it gives the same results when repeatedly used as a measuring instrument.

The specification of the outer model (measurement model, which represents the link between indicators and constructs) and inner model (structural model/substantive theory that connects latent variables) determines a latent variable score component (Ghozali & Latan, 2015).

Assessing the measurement model, particularly the outer model with reflective indicators, when utilising Partial Least Squares (PLS) involves evaluating the convergent and discriminant validity of the indicators. Furthermore, the composite dependability of the indication block is considered. The coefficient of determination (R2) is the primary measure used to assess the validity of the inner model. It quantifies the amount of variation that each endogenous latent variable can explain. The built model is assessed using Q2 predictive relevance and R2 value to gauge how effectively the model and its parameter estimates produce the observed values.

Considering the multitude of factors that impact purchase intentions, the research analysis faces multiple problems. Higher education problems are claimed to be impossible to explain using merely a bivariate analysis model with a single element. Furthermore, issues are highly personal and are impacted by various interconnected aspects, making them multifaceted (Asmin, 2002). These challenges inspire educational and social It is argued that the challenges in higher education cannot be adequately explained using only a simple analysis model with one factor. Additionally, these problems are highly individualized and influenced by multiple interconnected factors, thereby making them complex. Researchers to explore new strategies or procedures to improve the precision of their studies. Path analysis, which translates to path analysis (Sudaryono, 2011), is one of the new approaches in a multivariate analysis deemed efficient and helpful in conquering numerous relationship issues.

### ***Research Problem***

Based on research by Jia et al. (2020), it was found that the adoption of electric cars is still said to be low. The adoption of electric cars in Indonesia is still considered to be limited, even though environmental issues are increasing every year. There are several inconsistent research results regarding purchase intentions. Like the research of Tanuwijaya and Balqiah (2022), subjective norms have a positive effect on purchase intentions, whereas in the research of Huang and Ge (2019), there is no significant influence of subjective norms on purchases. Meaning. Therefore, researchers want to know what factors will influence the intention to purchase an electric car which will strengthen the results of previous research.

Partial Least Squares Structural Equation Modelling (PLS-SEM) is often used in corporate marketing research because of its capacity to estimate complex models with a limited sample size precisely.

Nevertheless, difficulties occur in its accurate implementation, particularly when considering its simultaneous emphasis on forecasting and elucidation. In contrast to consumer marketing, which relies on models such as the American Customer Satisfaction Index (ACSI) as benchmarks, using PLS-SEM in corporate marketing generates inquiries about the most effective structural equation modelling (SEM) techniques. The research extends to consumer behaviour, aiming to understand the intricate relationships between psychological constructs and purchase decisions, incorporating the moderating role of product knowledge. Despite employing advanced tools like SEM and PLS, challenges persist in nuanced applications in business marketing research. Additionally, traditional bivariate models need to catch up in higher education research, leading to the need for more precise methods. The path analysis emerges as a potential solution, addressing the multiplicity of factors influencing educational outcomes and enhancing the precision of analyses in both business marketing and higher education contexts.

### *Research Focus*

The research focused on unravelling the intricate relationships between psychological constructs and purchase decisions in the dynamic landscape of consumer behaviour. The study emphasised the interplay of perceived risk, environmental consciousness, and subjective norms in shaping consumers' purchase intentions, with a nuanced exploration moderated by product knowledge. The research employs advanced analytical tools, specifically Structural Equation Modelling (SEM) and Partial Least Squares (PLS), to achieve this. The research focuses on advancing our comprehension of consumer behaviour and decision-making processes to inform effective marketing strategies in a contemporary context.

### *Research Aim and Research Questions*

The aim was to provide a comprehensive and robust examination of perceived risk, environmental consciousness, and subjective norms on purchase intention, considering the moderating role of product knowledge. The understanding of the complex pathways influencing purchase intentions is vital in a market saturated with diverse products and heightened environmental considerations. This study contributes valuable insights to the academic discourse and offers actionable advice for companies aiming to effectively cater to the evolving preferences of socially responsible consumers.

The primary objective of the research is to determine the impact of perceived risk, environmental awareness, and subjective norms on purchase intention, with product knowledge acting as a moderating factor. This will be accomplished by route analysis utilizing structural equation modelling with these hypothesis developments:

**H1**: The Perceived Risk has a negative effect on Purchase Intention.
**H2**: The Environmental Consciousness has a positive effect on Purchase Intention.
**H3**: Subjective norms positively affect the purchase intention.
**H4**: The Perceived risk positively affects purchase intention through the moderating role of Product Knowledge.
**H5**: The Environmental Consciousness positively affects purchase intention through the moderating role of Product Knowledge.
**H6**: The Subjective Norm positively affects purchase intention through the moderating role of Product Knowledge.

## Research Methodology

### *General Background*

The path analysis (McDonald, 1996; Wright, 1921) allowed for estimating an equation system where every variable is observable. Unlike regression models, path models—also known as system regression models, can contain more than one dependent variable. Path model variables can be input as single-item constructions in Smart-PLS. A variable based on several indications is equally weighted to get a construct score. Theoretically, only structural connections, with or without control variables, between observable variables (or equally weighted constructs) are modelled. A moderation model is often used when one or more variables mediate between other variables. Moderated moderation can be modelled concurrently.

The path models may undergo significance testing thanks to bootstrapping in Smart-PLS. As a result, the PROCESS module offers every modeling and computation option that PROCESS has historically provided (Hayes, 2018). According to Sarstedt et al. (2020), Smart-PLS automatically builds PROCESS models, and the results are output instantly. Thus, additional computations are only needed in Smart-PLS. Here is an illustration of a PROCESS model in Smart-PLS.

### *Evaluation of the Measurement Model*

The measuring approach in this research employed reflecting indicators due to the influence of latent variable indicators on the observed indicators. The measurement model was assessed by examining the value in (Yamin, 2022):

a. The loading factor, called outer loading, represent the correlation between each measurement item and the variable. This statistic measures the item's ability to define or describe the measured variable accurately. Hair Jr et al. (2021) and Henseler et al. (2009) suggest that LF values of 0.70 are often acceptable. However, Chin (1998) presents an alternative perspective, stating that LF values larger than 0.50 are also considered good (valid).

b. The composite reliability (CR) is a measure that indicates the level of dependability of a variable, precisely its internal consistency. It is considered acceptable when it exceeds 0.6 (Henseler et al., 2009). According to Hair et al. (2011), the ideal Composite Reliability value is more than 0.70, while values between 0.60 and 0.70 are also considered acceptable.

c. The average variance extracted (AVE) is calculated by taking the average of the measurement items included in the variable. The degree to which the total variable accounts for the variability in the items used for measurement. This measure also serves as a demonstration of the variable's convergent validity. The AVE (Hair et al., 2021) should be more than 0.50.

d. The discriminant validity refers to the extent to which the studied variables or constructs differ from other variables or constructs subjected to statistical analysis. The evaluation of the discriminant validity occurs at both the variable and indicator levels. The Fornell-Lacker Criterion compares the average variance extracted (AVE) root with the correlation between variables. This criterion is implemented at the variable level, whereas cross-loading measurement is accomplished at the indicator level. The Heterotrait Monotrait Ratio (HTMT) is another metric to assess the discriminant validity. This study assesses the validity of HTMT, which is expected to be below 0.9 based on the findings of Henseler et al. (2013) and Hair et al. (2021).

### *Structural Model Evaluation*

This structural model evaluation aims to examine the hypothesis (or causation). The bootstrapping procedure was used for the hypothesis testing (percentile approach). The t-test is the statistical test applied in this methodology. The two-way test's (two-tailed test) t-values show that the test is 1.96 (significant threshold = 5%). The t-test test requirements state that a link between variables is considered to have a substantial impact if the value of $tstabstik > ttael$ or the significance value <0.05

(Yamin, 2022).

Multiple linear regression tests the effect of two or more independent variables on one dependent variable. Testing the relationship between the influence of risk perception (X1), environmental awareness (X2), and subjective norms (X3) on purchase intention (Y) moderated by the product knowledge (Z)is carried out to answer all hypotheses in this study as follows:

$$Y_{it} = \alpha + \beta_1 X_{1it} + \beta_2 X_{2it} + \beta_3 X_{3it} + \varepsilon_{it} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

$$Y_{it} = \alpha + \beta_1 X_1 Z_{it} + \beta_2 X_2 Z_{it} + \beta_3 X_3 Z_{it}\ \varepsilon_{it} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

***Evaluation of Model Quality and Fit***

Assessing the model's quality involves analysing the model. The model's acceptability may be evaluated by many metrics, including R square, Q square, F square, and SRMR (Yamin, 2022).

1. R square

The R square value measures the combined influence of external and internal factors on the dependent variables in the model. According to Chin (1998), the R honest value is 0.67, which suggests a high correlation; 0.33, which offers a moderate connection; and 0.19, which means a low correlation.

2. F square

Quantifies the extent of impact exerted by the variables in the structural model or the exogenous latent variables on the endogenous variables. This metric is determined by comparing the R square value obtained when variables are included or deleted from the structural model. The F honest value in Hair et al. (2021) might be interpreted as 0.02 (indicating a small effect size), 0.15 (indicating a medium effect size), or 0.35 (indicating a large effect size).

**Research Results**

The Measurement Model evaluation established the connection between a conceptual idea and the specific measurements used to represent it. The determination of data validity and reliability relied on measurement models. Two validity tests, namely the convergent validity and the discriminant validity were used to evaluate the measurement model.

***Evaluation of the Measurement Model (Outer Model)***

The outer loading describes how effectively goods reflect/describe variable measures. Chin (1998) states that an external loading value of 0.50 is deemed acceptable or legitimate. Table 1 shows the outer loading value of this study:

**Table 1**

*The outer Model*

| No | Variables | Item | *Outer loadings* | |
|---|---|---|---|---|
| 1 | X1 | X1.1 | 0,842 | Valid |
| | | X1.2 | 0,884 | Valid |
| | | X1.3 | 0,843 | Valid |
| | | X1.4 | 0,919 | Valid |
| | | X1.5 | 0,929 | Valid |
| | | X1.6 | 0,904 | Valid |
| | | X1.7 | 0,869 | Valid |
| | | X1.8 | 0,932 | Valid |
| | | X1.9 | 0,891 | Valid |
| | | X1*Z | 1,216 | Valid |

| | | | | |
|---|---|---|---|---|
| 2 | X2 | X2.1 | 0,842 | Valid |
| | | X2.2 | 0,912 | Valid |
| | | X2.3 | 0,888 | Valid |
| | | X2.4 | 0,914 | Valid |
| | | X2.5 | 0,858 | Valid |
| | | X2.6 | 0,833 | Valid |
| | | X2.7 | 0,859 | Valid |
| | | X2.8 | 0,927 | Valid |
| | | X2.9 | 0,917 | Valid |
| | | X2*Z | 1,788 | Valid |
| 3 | X3 | X3.1 | 0,868 | Valid |
| | | X3.2 | 0,891 | Valid |
| | | X3.3 | 0,774 | Valid |
| | | X3.4 | 0,909 | Valid |
| | | X3.5 | 0,885 | Valid |
| | | X3.6 | 0,913 | Valid |
| | | X3.7 | 0,924 | Valid |
| | | X3.8 | 0,921 | Valid |
| | | X3.9 | 0,925 | Valid |
| | | X3.10 | 0,913 | Valid |
| | | X3.11 | 0,895 | Valid |
| | | X3.12 | 0,891 | Valid |
| | | X3*Z | 1,614 | Valid |
| 4 | Y | Y1 | 0,896 | Valid |
| | | Y2 | 0,900 | Valid |
| | | Y3 | 0,799 | Valid |
| | | Y4 | 0,899 | Valid |
| | | Y5 | 0,841 | Valid |
| | | Y6 | 0,925 | Valid |
| | | Y7 | 0,899 | Valid |
| | | Y8 | 0,916 | Valid |
| | | Y9 | 0,906 | Valid |
| | | Y10 | 0,913 | Valid |
| 4 | Z | Z1 | 0,706 | Valid |
| | | Z2 | 0,865 | Valid |
| | | Z3 | 0,673 | Valid |
| | | Z4 | 0,855 | Valid |
| | | Z5 | 0,936 | Valid |
| | | Z6 | 0,882 | Valid |
| | | Z7 | 0,912 | Valid |
| | | Z8 | 0,941 | Valid |
| | | Z9 | 0,880 | Valid |
| | | Z10 | 0,909 | Valid |
| | | Z11 | 0,934 | Valid |
| | | Z12 | 0,916 | Valid |

Based on this table, all measurement items on each variable, both perceived risk, environmental consciousness, subjective norm, purchase intention, and product knowledge, show an outer loading value> 0.5, so it can be said that all indicators used are valid.

The Average variation Extracted measures the amount of variation in the measurement items that can be attributable to the overall variable, whereas the Composite dependability evaluates the level of reliability of the variable. The table below presents the values for Composite Reliability and Average Variance Extracted:

**Table 2**

*The Composite Reliability and the Average Variance Extracted*

| | Composite Reliability | Average Variance Extracted (AVE) |
|---|---|---|
| X1 | 0,972 | 0,794 |
| X1*Z | 1,000 | 1,000 |
| X2 | 0,970 | 0,781 |
| X2 *Z | 1,000 | 1,000 |
| X3 | 0,979 | 0,798 |
| X3* Z | 1,000 | 1,000 |
| Y | 0,973 | 0,786 |
| Z | 0,974 | 0,760 |

Based on the table provided, it can be observed that the Composite dependability value for all study variables is higher than 0.7, which suggests that the dependability level is considered satisfactory. Overall, items that measure perceived risk, environmental consciousness, subjective norm, purchase intention, and product knowledge variables are consistent in measuring these variables. Furthermore, the average value (AVE) of all research variables exceeds 0.5, indicating that the level of variation in all items within these research variables meets the criteria for satisfactory convergent validity.

The discriminant validity test illustrates how far the variables or constructs that are built are different from other variables/constructs and are statistically tested. This test can be done by looking at the HTMT (Heterotrait Monotrait Ratio) value in the following table:

**Table 3**

*HTMT (Heterotrait Monotrait Ratio)*

| | PR | PR* PK | EC | EC*PK | SN | SN*PK | PI |
|---|---|---|---|---|---|---|---|
| **PR** | | | | | | | |
| **PR* PK** | 0,133 | | | | | | |
| **EC** | 0,222 | 0,233 | | | | | |
| **EC* PK** | 0,157 | 0,437 | 0,677 | | | | |
| **SN** | 0,220 | 0,216 | 0,956 | 0,594 | | | |
| **SN* PK** | 0,163 | 0,455 | 0,663 | 0,989 | 0,584 | | |
| **PI** | 0,265 | 0,217 | 0,860 | 0,567 | 0,896 | 0,565 | |
| **PK** | 0,155 | 0,294 | 0,742 | 0,556 | 0,718 | 0,519 | 0,66 0 |

The table shows that the HTMT value of all pairs of variables is smaller than 0.9, so the discriminant validity is fulfilled. This means that the correlation between measurement items in measuring the same variable is stronger than the correlation between items and other variable items, in other words, measurement items are more correlated with the measured construct than other constructs.

**Table 4**

*Fornell-Larcker Criterion*

| | PR | PR*PK | EC | EC*PK | SN | SN*PL | PI | PK |
|---|---|---|---|---|---|---|---|---|
| **PR** | 0,891 | | | | | | | |
| **PR*PK** | -0,134 | 1,000 | | | | | | |
| **EC** | -0,218 | 0,229 | 0,884 | | | | | |
| **EC*PK** | 0,155 | -0,437 | -0,664 | 1,000 | | | | |
| **SN** | -0,220 | 0,214 | 0,932 | -0,587 | 0,893 | | | |
| **SN*PK** | 0,161 | -0,455 | -0,650 | 0,989 | -0,577 | 1,000 | | |
| **PI** | -0,268 | 0,213 | 0,836 | -0,556 | 0,875 | -0,554 | 0,887 | |
| **PK** | -0,139 | 0,288 | 0,725 | -0,549 | 0,708 | -0,513 | 0,646 | 0,872 |

The table above displays the AVE root value of each variable along the diagonal axis. It indicates that all variables have an AVE root value that exceeds their correlation with other variables. To assess the discriminant validity of the study variables.

The bootstrapping process is used to assess structural models or examine hypotheses using the percentile approach. The t-test is the statistical test applied in this methodology. The two-way test's (two-tailed test) t-values show that the test is 1.96 (significant threshold = 5%). The t-test test requirements state that the hypothesis is accepted if the value *tstabstik> ttael* or the significance value <0.05. The following tables and figures show the structural model testing results:

**Figure 1**

*Outer Model*

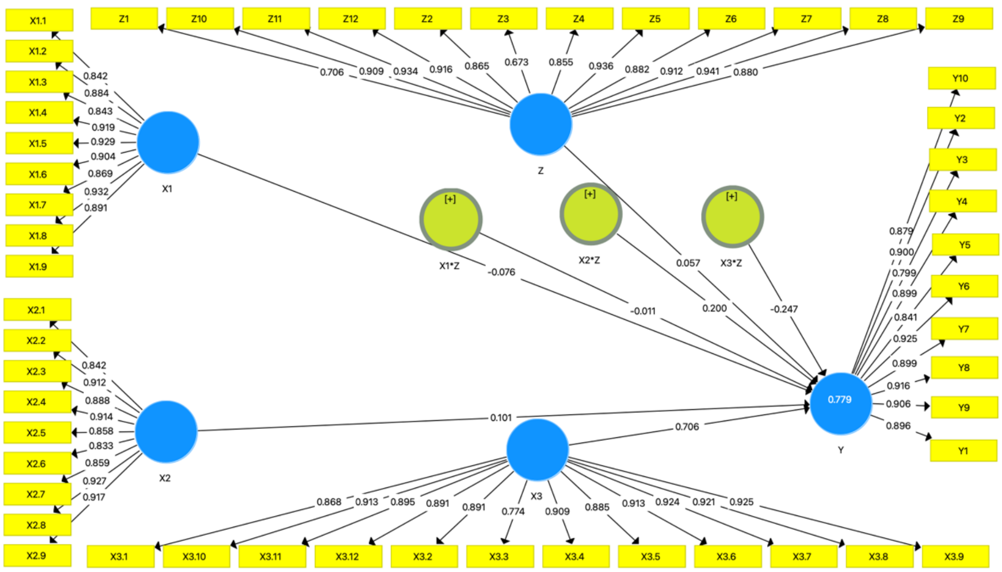

**Table 5**

*Hypothesis Test Results*

| | Coefficients | T Statistics | P Values | |
|---|---|---|---|---|
| X1 -> Y | -0,076 | 0,987 | 0,324 | Not Significant |
| X1 *Z -> Y | -0,011 | 0,135 | 0,892 | Not Significant |
| X2 -> Y | 0,101 | 0,478 | 0,633 | Not Significant |
| X2 * Z -> Y | 0,200 | 0,637 | 0,524 | Not Significant |
| X3 -> Y | 0,706 | 3,520 | 0,000 | Significant |
| X3* Z -> Y | -0,247 | 0,713 | 0,476 | Not Significant |

Based on the figure and table above, the relationship between variables (hypothesis test results) can be explained as subjective norms playing a more dominant role than the risk perception and environmental awareness factors in the context of purchase intention. However, the interaction between these factors and product knowledge does not have a significant impact except the subjective norm on purchase intention.

The R-squared value is used to quantify the total impact of exogenous and endogenous factors on other endogenous variables in the model. Below is a tabulated representation of the R square values obtained in this study:

**Table 6**

*R Square*

| | R Square | R Square Adjusted |
|---|---|---|
| Y | 0,779 | 0,742 |

The provided data indicates that the perceived risk, environmental awareness, and subjective norm all account for 77.9 percent of the effect on purchase intention, placing it in the high category.

**Table 7**

*F Square*

| | Y |
|---|---|
| X1 | 0,025 |
| X1*Z | 0,001 |
| X2 | 0,005 |
| X2 * Z | 0,011 |
| X3 | 0,282 |
| X3*Z | 0,013 |

The table shows that perceived risk, environmental consciousness, and subjective norm have a low influence (F square = 0.025, 0.005, 0.282) on the purchase intention, as well as the mediating role of product knowledge on the influence of perceived risk, environmental consciousness, and subjective norm has a low influence (F square = 0.001, 0.011, 0.013) on purchase intention.

## Discussion

Based on the findings from Table 5, it can be concluded that there is no statistically significant impact of perceived risk on purchase intention. This means that consumers may have a higher level of understanding and acceptance of risk for the product or service under study (Rithmaya, 2016).

Consumers have built in-depth knowledge about a particular product or service, so perceived risk is not a significant determining factor in forming the purchase intentions (Bangun et al., 2023). In contrast to previous research, perceived risk negatively affects consumers' intentions to purchase electric vehicles (Jiang et al., 2021). Based on the findings from Table 5, the same results of hypothesis testing show that environmental consciousness does not significantly affect purchase intention. Environmental consciousness may be a minor factor influencing purchase decisions (Kusumawati & Tiarawati, 2022). While awareness of environmental issues can be a positive value, consumers' purchase intentions may need to be more directly driven (Kristiana & Diana, 2023). Consumers may be more influenced by other factors, such as product quality, price, or functional needs, which may predominate in their purchase decision-making. Several potential factors could explain this difference in results. Additionally, several empirical research studies demonstrate a positive correlation between the intent to purchase environmentally friendly products and environmental consciousness (Chen & Chang, 2012; Walker et al., 2013). Research by Tanuwijaya and Balqiah (2022) found that environmental consciousness positively influenced purchase intention. Differences in SEM-PLS analysis methods may create different results compared to previous studies that may have used different statistical analysis approaches. In addition, differences in the research sample, respondent characteristics, or market context may also play a key role. This variability may result in differences in consumer perceptions of risk and purchase intentions, leading to contrasting results.

According to Table 5, the data obtained from hypothesis testing indicate a significant impact of subjective norm on purchase intention. According to the Theory of Planned Behaviour can be measured through indicators derived from measuring subjective norms according to Wedayanti and Giantari (2016) as follows: belief in the role of family in starting a business, confidence in friends' support in industry, faith in support from teachers, confidence in support from successful entrepreneurs, trust in business support from people who are considered essential. Subjective norms refer to the positive or negative evaluations from external society or reference groups that a person receives when adopting specific behaviour (Ajzen, 1991). In line with Tanuwijaya and Balqiah (2022), subjective norms positively influence purchase intention. These significant findings further confirm and strengthen previous research conducted through the PLS-SEM method, providing additional insights into the relationship between social norms and consumer purchasing decisions and enhancing our understanding of this dynamic.

Based on Table 5, the results of hypothesis testing show that product knowledge cannot moderate the relationship between perceived risk, environmental consciousness, and subjective norm on purchase intention. This discovery implies that the level of consumer product knowledge has no effect on the impact of perceived risk, environmental consciousness, and subjective norms on the inclination to make a purchase. Although the product knowledge is generally considered a factor influencing purchasing decisions, the variable did not act as a significant modulator in this study. This has important implications for designing marketing strategies, as it suggests that efforts to increase consumers' product knowledge may not directly improve their purchase intentions in the face of perceived risk, environmental awareness, or subjective norms. To promote such new technology schemes, there must be complete knowledge of the various factors that motivate consumers and early adopters to purchase BEVs to meet their needs. However, these factors differ in each country due to differences in culture, governance, policy aspects, environmental differences, and product life cycle aspects. Recognising that a significant portion of society may harbour skepticism towards new technologies is crucial, primarily driven by their limited understanding (Gärling and Thøgersen, 2001). In research Pradeep et al. (2021), found that maintenance knowledge does not have a direct influence on purchase intentions. In this research, there was also no influence of product knowledge as a moderating variable on purchase intentions. Therefore, companies need to consider a more holistic marketing approach, which includes aspects of product knowledge and considers how other factors interact and influence each other in shaping consumer preferences.

The study utilised Structural Equation Modelling (SEM) Partial Least Squares (PLS) to explore the relationship between perceived risk, environmental consciousness, subjective norm, product knowledge, and purchase intention. Scientific papers by Hair et al. (2017) and Martínez-López et al. (2013) were cited to support the recognition and acceptance of SEM-PLS in marketing research. However, the study identifies challenges and issues in applying PLS-SEM appropriately, emphasizing the need for a nuanced understanding of when and where to use it. Covariance-based SEM is presented as a feasible alternative. As presented in the literature, the critical evaluation of SEM methods sets the stage for the study's contribution to understanding consumer behaviour.

The study compares its results with the findings of other researchers, referencing relevant literature throughout the discussion. The results indicate that perceived risk and environmental consciousness do not significantly affect purchase intention. This contrasts with some earlier studies that found a negative impact of perceived risk on purchase intentions in specific contexts. The discussion provides possible explanations for these differences, including variations in consumer knowledge and contextual factors. It highlights the dynamic nature of consumer behaviour and the need for a context-specific understanding. The significant impact of subjective norms on purchase intention aligns with established theories, such as the Theory of Planned Behaviour, corroborating prior research. This consistency strengthens the validity of the study's findings.

The discussion identifies unexplored aspects of the scientific problem that could be avenues for future research. One key aspect is the non-significant moderating role of product knowledge. The study implies that purchase intentions may not be directly affected by efforts to improve product knowledge, as factors such as perceived risk, environmental awareness, or subjective norms play a significant role. This opens opportunities for further investigation into alternative moderators or additional factors that may influence the relationship between product knowledge and purchase intention. Additionally, the study emphasises the need for a holistic marketing approach, indicating a direction for future research to explore integrated strategies that consider multiple influencing factors simultaneously.

The study recognises its limitations, such as focusing on a specific context and the potential influence of various external factors. It acknowledges the complexity of consumer behaviour and the multifaceted nature of purchase decisions. These limitations ensure transparency regarding the study's limitations and help to facilitate a more nuanced interpretation of the findings. Future research could address these limitations by exploring diverse contexts, considering additional variables, and employing complementary research methods.

## Conclusions and Implications

This research successfully demonstrated the implementation of SEM-PLS analysis to test the model in the context of purchase intention and its factors. The Smart-PLS 3 software facilitated a comprehensive and transparent evaluation of the measurement and structural models. The results of this study have important implications for research and practitioners in applying SEM PLS.

The confirmed reliability and validity of the measurement model underscore the credibility of the identified variables. For businesses, this implies the need for meticulous attention to the factors influencing consumer behaviour, particularly subjective norms, which emerged as a pivotal determinant of purchase intention. Recognising the limited impact of perceived risk and environmental consciousness, managerial strategies should pivot toward harnessing the power of social influences. Marketing campaigns highlighting subjective norms, such as social approval and peer endorsements, can significantly impact consumer decision-making. Additionally, the non-significant moderating role of product knowledge emphasises the importance of other factors in shaping the purchase intention. Businesses are advised to invest in continuous consumer education initiatives to bolster product knowledge, although its direct moderating influence might be limited.

## Suggestions for Future Research

A potential area for future research could explore the use of a mixed-methods approach to achieve a thorough understanding of the identified variables. Combining qualitative methods, such as in-depth interviews or focus group discussions, with the quantitative data used in structural equation modelling could offer richer insights into the intricacies of consumer decision-making processes. Qualitative methods may help uncover nuanced aspects of perceived risk, environmental consciousness, subjective norm, and product knowledge that quantitative measures might not fully capture. Additionally, incorporating real-time data collection methods, such as mobile ethnography or ecological momentary assessment, could provide a more dynamic and contextually grounded perspective on consumer behaviour. This approach would contribute to a more holistic understanding of the factors influencing the purchase intention, enhancing the robustness of the research findings.

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