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Original scientific paper

Understanding Diverse E-commerce Behavior in Emerging Markets

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Abstract: This study aims to examine the factors influencing online purchase intentions in emerging markets and to explore distinct consumer segments based on these factors. Utilizing the Theory of Planned Behavior and PLS-SEM, the research analyzes data from 1596 participants collected through a structured questionnaire. Additionally, the Pathmox algorithm identifies three unique behavioral patterns, segmenting consumers based on household demographics, including the number and age of children. The results indicate that 70% of the variance in online purchase intentions can be explained by attitude, perceived behavioral control, subjective norms, and perceived trust, with the influence of these factors varying across different segments. In the first two segments, the variance in shopping intentions is explained by the same set of factors but with different weights - 73% and 62%, respectively. In the third segment, the variance is explained solely by attitude and subjective norms, accounting for 69%. These findings suggest that a one-size-fits-all approach is unsuitable for emerging markets, highlighting the need for tailored marketing strategies. This study is pioneering in e-commerce research, leveraging the Pathmox algorithm to elucidate the complex interplay of consumer attitudes and demographics in shaping online shopping behavior.

Keywords: e-commerce behavior; pathmox algorithm; PLS-SEM

1 INTRODUCTION

E-commerce is vital in integrating businesses and consumers, facilitating communication, and sharing information [1]. In emerging countries, e-commerce drives economic development, fostering entrepreneurship, innovation, and employment opportunities [2]. The COVID-19 pandemic significantly boosted online sales, transforming e-commerce worldwide. However, in some countries, online purchases are still in their beginnings, requiring careful study of the factors influencing customers' online purchase behavior [3].

Data science algorithms have shown effectiveness in predicting consumer purchasing behavior in e-commerce [4]. Yet, their application alone may not significantly improve prediction accuracy due to factors like consumer behavior complexity and sample heterogeneity. This study explores a novel data science technique to address this heterogeneity within the context. Specifically, this study aims to examine the factors that affect online purchase intentions in emerging markets and identify distinct consumer segments based on these factors.

The study's conceptual framework is grounded in the Theory of Planned Behavior, utilizing the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach to analyze causal relationships among latent variables [5]. Additionally, the Pathmox algorithm is used to explore heterogeneity in consumer behavior.

The remainder of the document is organized as follows: first, a literature review; next, the research methodology followed by the presentation of results; and finally, a discussion of implications, limitations, and potential areas for further research.

2 LITERATURE REVIEW

2.1 Theory of Planned Behavior

The Theory of Planned Behavior (TPB), developed by psychologist Icek Ajzen in the late 1980s, is a widely recognized framework for understanding and predicting human behavior, particularly in decision-making. TPB posits that individuals make deliberate choices based on their attitudes, perceived social norms, and perceived behavioral control, collectively shaping their intentions and subsequent behavior. TPB suggests that positive attitudes, perceived social pressure and control over execution increase the likelihood of engaging in a behavior.

Attitude (AT) is the degree to which a person evaluates or appraises the conduct of an issue positively or negatively [6]. While attitudes may not always directly predict purchase behavior [7], their multifaceted nature, comprising cognitive, emotional, and intentional aspects, is fundamental [8]. These attitudes can relate to adopting the Internet as a shopping medium or the appeal of specific online retailers, often influenced by perceived risks [9].

Perceived control (PC) is the belief that a person can control the execution of a particular activity [10]. PC is crucial in understanding consumer behavior, especially online shopping, resulting from interaction with website features. It has significantly impacted individuals' perceptions of risk, stress, and overall well-being. Also, PC has notably enhanced consumers' perceptions of control through service innovation, which can lead to a more favorable purchase decision, as past research has indicated [11].

Subjective norms (SN) reflect perceptions of social pressure to engage in a behavior [12]. These norms significantly shape decision-making, with people more likely to adopt a behavior if their role models endorse it [13]. Although exploring factors driving online purchases is limited [14], research highlights the beneficial impact of SN from friends, family, and coworkers on online purchasing behavior [34]. Their findings suggest that when consumers perceive support for online purchases from their peers, it fuels their desire to make such purchases, underscoring the subjective and culturally influenced nature of these perceptions [15]. Recent studies explore cultural perspectives on how SN affects behavioral intentions related to technology use [16].

2.2 Perceived Trust

Perceived trust (PT) is an individual's subjective assessment of another entity's reliability, dependability, and credibility. It is based on past experiences, interactions, reputation, and communication and is crucial in various contexts.

Studies underscore PT's pivotal role in shaping consumer behavior within online environments, positively impacting online purchase intentions and facilitating smoother transactions [17, 18]. Furthermore, it fosters a sense of security and comfort for consumers, especially when engaging with trusted e-commerce entities [19]. Moreover, PT simplifies the complexity of the online shopping experience and streamlines decision-making, thereby enhancing purchase intentions [20]. Additionally, it influences other factors such as reputation, price advantages, and user-generated content, contributing to customer trust and behavior [21]. Given the extensive body of research highlighting the significance of PT in online commerce, understanding its role is essential for creating a favorable online shopping environment [22]. PT affects the decision to purchase and shapes the overall perception of online shopping. It helps establish positive customer expectations while meeting vendor expectations and influencing customer attitudes toward online purchases.

2.3 Uncovering Heterogeneity in Online Shopping with Pathmox

PLS-SEM is a robust approach for analyzing online purchase acceptance dynamics, positing that exogenous variables elucidate endogenous variables without significant influence from other factors. However, this notion often requires practical validation [23]. Recognizing the potential presence of heterogeneous information structures and identifying unobserved heterogeneity within the target population is crucial for effectively analyzing and assessing PLS-SEM outcomes [24]. Conclusions drawn about the studied phenomenon through a single model utilizing aggregate-level data can only be deemed valid if it is established that this heterogeneity does not impact the findings [23]. Several studies have elucidated the presence of heterogeneity in online shopping, attributing it to individual differences in consumer behavior and preferences [25]. Each consumer's unique needs, tastes, and preferences create personalized and distinct purchasing behavior. This heterogeneity may be manifested as either observed or unobserved, with several studies underscoring the significance of unobserved heterogeneity in online shopping. Moreover, personal and subjective factors can influence consumer preferences and purchasing behavior in challenging-to-measure or control ways [26, 27]. Hence, a deeper comprehension of unobserved heterogeneity is imperative for enhancing the online consumer experience and refining more precise and effective online shopping models.

In PLS-SEM analysis, accounting for the heterogeneity of a population typically entails dividing it into homogeneous segments. There are two main techniques for performing this segmentation. Firstly, observations can be predetermined to belong to specific details based on variables designated for that purpose. This segmentation approach has been widely used in various applications, including multi-group analysis proposals (PLS-MGA), first introduced by [28]. However, identifying a variable that explains the heterogeneity of behaviors is often challenging. Segmentation based on a priori information can be limited by the absence of a substantive theory regarding the variables that drive the heterogeneity [29]. At other times, this cause cannot be observed sufficiently to capture and explain heterogeneity [30]. Several techniques, commonly called latent class techniques, have been developed in PLS-SEM to overcome these limitations for identifying and addressing unobserved heterogeneity [29].

The Pathmox algorithm, recently proposed, draws near a priori approaches by requiring external explanatory variables to account for heterogeneity. Pathmox can detect heterogeneity when many segmentation variables are present and identifying the responsible variables is challenging [31]. The algorithm creates a tree with various models in each node, iteratively establishing significant differences.

Pathmox operates as follows:

1. An overall PLS-SEM model is fit for all data to define the tree root.
2. The algorithm creates all allowed partitions for each node, considering segmentation variables.
3. Iteratively, models with significant differences in each child node are established.

To avoid overfitting the model, the algorithm requires three parameters: the significance threshold (usually set at 0.05), the minimum number of individuals per node (determined empirically based on the sample size), and the maximum number of levels the tree can grow. An F-test defines optimal partitions and binary splits for regression patterns, indicating homogeneity in the parent node model and heterogeneity in child node models.

To gain a more scholarly understanding of the Pathmox algorithm, let's delve into its operational principles:

```
Pathmox <- function(node) {
   repeat {
      for (child_node in node.children) {
evaluate_outer_models_equivalence by F_test
         if (distinct_outer_models == TRUE) {
reestimate_PLS_SEM_model(child_node)
Pathmox(child_node)
         } else {
            stop <- TRUE
         }
      }
   } until (stop)
Pathmox(global_PLS_SEM_model)
}
```

However, Pathmox can only identify significant models based on available sources of heterogeneity and cannot confirm statistically significant differences post hoc. Lamberti proposed a hybrid multigroup approach in three steps: determining segmentation variables via Pathmox, estimating PLS-SEM models for the segmentation, and conducting PLS-MGA path coefficient comparisons for each segment [31].

3 RESEARCH METHODOLOGY

3.1 Research Model

The proposed research model, illustrated in Fig. 1, posits that four independent variables explain online purchase intention (OPI). Various segments exist within this model. Based on the literature review, we propose the following hypotheses and propositions:

- H1: Attitude has a significant and positive impact on Online purchase intention.
- H2: Perceived Control has a significant and positive impact on Online purchase intentions.
- H3: Subjective Norms have a significant and positive impact on Online purchase intention.
- H4: Perceived Trust has a significant and positive impact on Online purchase intention.
- P0: There is heterogeneity in the model explaining consumers' Online purchase intention.

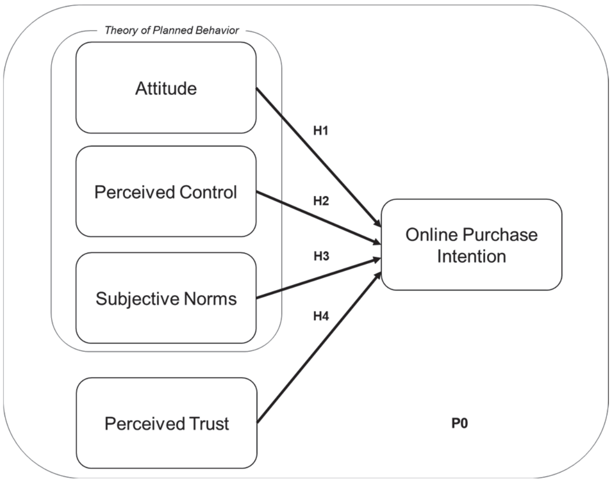

Figure 2 The proposed research model

3.2 Scales

The scale used to measure online purchase intention (OPI) has been developed using [31]. AT has been measured through a scale adjustment proposed by [32]. Items of the research carried out by [32] were used to assess SN and PC. Finally, the proposal of [33] was used to measure PT.

3.3 Data Collection and Sample

The sample includes 875 men and 721 women, with a mean age of 38.2 years. Tab. 1 presents an overview of the sample data.

Table 1 Sample description

Variable	Mean / N	SD / percentage
Age	38.2	12.4
Gender		
Male	875	54.8%
Female	721	45.2%
Education		
Primary	24	1.5%
Secondary	175	11.0%
Tertiary	1397	87.5%
Relationship Status		
Married/with Partner	713	44.7%
Single	883	55.3%

4 RESULTS
4.1 PLS-SEM

The analysis was done with the help of SmartPLS [35]. Tab. 2 shows the measurement model analysis for latent variables. The cutoff points are based on [36]. AT has been deemed reliable and valid due to its high composite reliability (0.93) and Cronbach's alpha (0.88) scores, as well as its high AVE (0.81). The factor loadings, which indicate the effectiveness of measuring the underlying construct, are also considered strong, with values above 0.7. Similarly, OPI shows good convergent validity with high composite reliability (0.93), Cronbach's alpha (0.89) score, and a high AVE (0.82). PC also shows promising results with a good AVE of 0.74, strong composite reliability (0.90), and Cronbach's alpha (0.83) scores. Factor loadings indicate that the construct remains both reliable and valid. SN is also reliable, with a composite reliability score of 0.88 and Cronbach's alpha of 0.80, a good AVE of 0.71, and an accurate construct measurement. The PT construct also shows favorable results with a high AVE of 0.78 and elevated values for composite reliability (0.91) and Cronbach's alpha (0.86), indicating reliability and validity.

Table 2 Estimation of the metrics of the measurement model

Latent Variable	Metric / Items	Value / λ
AT	AVE	0.81
	Composite Reliability	0.93
	Cronbach's Alpha	0.88
	AT1	0.87
	AT2	0.91
	AT3	0.91
OPI	AVE	0.82
	Composite Reliability	0.93
	Cronbach's Alpha	0.89
	OPI1	0.92
	OPI2	0.92
	OPI3	0.88
PC	AVE	0.74
	Composite Reliability	0.90
	Cronbach's Alpha	0.83
	PC1	0.79
	PC2	0.91
	PC3	0.88
SN	AVE	0.71
	Composite Reliability	0.88
	Cronbach's Alpha	0.80
	SN1	0.85
	SN2	0.86
	SN3	0.83
PT	AVE	0.78
	Composite Reliability	0.91
	Cronbach's Alpha	0.86
	PT1	0.89
	PT2	0.88
	PT3	0.88

The Fornell-Larcker criterion is a method to evaluate the discriminant validity of the measurement model. According to Fornell and Larcker, the square root of the AVE for each latent variable must be greater than its correlations with other latent variables [37]. This indicates that the latent variables are distinct from one another and measure unique aspects of the construct. Tab. 3 suggests that the latent variables in the research model have good discriminant validity. Each latent variable has a higher AVE than its correlations with other latent variables, indicating that they measure unique aspects of the construct. Tab. 4 displays conclusive evidence for discriminant validity, as all Heterotrait-monotrait (HTMT) ratios of correlation values were below 0.50. The HTMT ratio of correlation is a reliable way to evaluate the discriminant validity of a structural equation model. This method compares the correlations among items within a construct against the correlations among items across different constructs. A ratio lower than 0.9 signifies strong discriminant validity [38, 39]. The HTMT ratio results reveal that the correlations between items within each construct are stronger than the correlations between items across constructs, as all ratios are less than 0.9.

Table 3 Discriminant validity test (Fornell-Larcker)

Latent Variable	AT	OPI	PC	SN	PT
AT	0.90				
OPI	0.80	0.90			
PC	0.61	0.65	0.86		
SN	0.62	0.64	0.53	0.85	
PT	0.49	0.53	0.50	0.48	0.88

Table 4 Discriminant validity test (HTMT ratio of correlations)

Latent Variable	AT	OPI	PC	SN
OPI	0.89			
PC	0.72	0.76		
SN	0.73	0.76	0.65	
PT	0.56	0.60	0.59	0.58

Tab. 5 summarizes the structural results. We used a bootstrapping procedure with 5000 subsamples to produce the path coefficients and corresponding t-values and p-values. The determination coefficient value (R^2) for the OPI was 0.70. PLS-SEM results confirm that the latent variables in the model are positively associated with the OPI and that the model accounts for a large proportion of the variance in OPI.

Table 5 PLS structural results

Hyp.	Relationship	Path coefficient	t-value	p-value
H1	AT ->OPI	0.53	19.7	0.00
H2	PC->OPI	0.18	7.5	0.00
H3	SN ->OPI	0.17	7.2	0.00
H4	PT ->OPI	0.09	4.8	0.00
	OPI R^2	0.70		

4.2 Pathmox Analysis

The Pathmox algorithm was utilized to identify distinct groups in a model of e-commerce acceptance. Pathmox analysis was performed on the following variables: Age, Gender, Internet access, Educational level, Marital status, Number of cohabitants, Number of children, and whether the individual had traveled to another country for leisure in the last year.

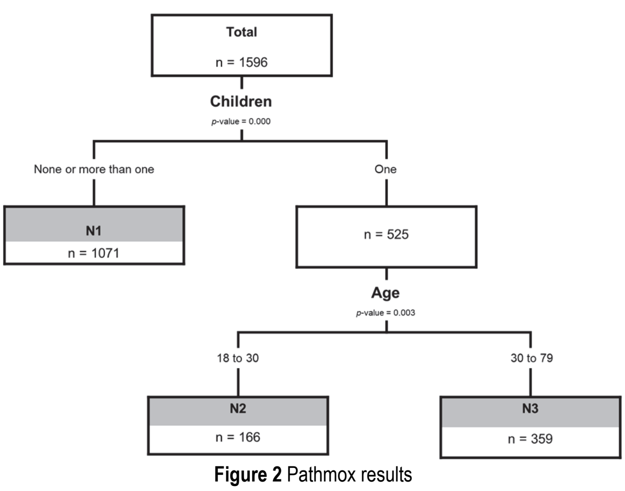

Figure 2 Pathmox results

Fig. 2 reveals the analysis result, which identified three distinct groups of individuals based on the number of children in their households and their ages: Group N1 includes 1071 individuals who either have no children or have more than one child. Group N2 comprises 166 young individuals aged between 18 and 30, each with a single child. Finally, group N3 comprises 359 adults aged 31 to 79, each with a single child.

Tab. 6 displays the structural results of the analysis conducted for each group, revealing that AT has a significant positive impact on the OPI for all three groups, with N1 demonstrating the strongest effect (0.59), followed by N3 (0.51) and N2 (0.31). PC also significantly positively impacts the OPI for two groups, with N2 demonstrating the strongest effect (0.28), followed by N1 (0.19). However, for N3, the effect is positive but not statistically significant (0.09, ns). SN has a significant positive impact on the OPI for N1 (0.11), N2 (0.24), and N3 (0.31), while PT has a significant positive effect on the OPI for N1 (0.09) and N2 (0.14), but not for N3 (0.07, not significant).

Table 6 PLS structural results by groups (Path coefficients and R^2)

Relationship	N1	N2	N3
AT ->OPI	0.59^{***}	0.31^{***}	0.51^{***}
PC->OPI	0.19^{***}	0.28^{***}	0.09^{ns}
SN ->OPI	0.11^{***}	0.24^{***}	0.31^{***}
PT ->OPI	0.09^{***}	0.14^{***}	0.07^{ns}
OPI R^2	0.73	0.62	0.69

Notes: ***: p-value < 0.000; ns: non-significant

Upon further examination, it becomes evident that the impact of attitude towards online shopping on the OPI is strongest for group N1, while SN has the lowest effect in this group. The online shoppers in group N1 are characterized by an average age of 38.12 years, with the majority having access to the Internet and tertiary education. On the other hand, for group N2, the impact of attitude towards online shopping on the OPI is the weakest compared to the other two groups, while perceived control has a more significant impact. The online shoppers in group N2 are younger, with an average age of 24.42 years, and mostly single women with access to the internet and tertiary education. For group N3, the impact of SN on the OPI is the strongest compared to the other two groups, while perceived control has the lowest effect. The online shoppers in group N3 are characterized by an average age of 44.73 years, with the majority being women with access to the internet and tertiary education and married.

Furthermore, we analyzed variance (ANOVA) to examine any significant differences in the mean scores of the latent variables of the model among the three groups. The findings indicate that there were no statistically significant differences between the groups.

Before conducting PLS-MGA, we performed the MICOM procedure to establish measurement invariance. The results showed partial measurement invariance, which allowed for multigroup analysis. Tab. 7 indicates a statistically significant difference in one path between N1 and N2, as well as between N1 and N3 and N2 and N3. These differences highlight the importance of considering age and family composition when examining e-commerce acceptance.

The findings from this study confirm the validity of hypotheses H1, H2, H3, and H4. A significant outcome of this research is the discovery that AT notably positively impacts the OPI for all three distinct groups. Conversely, the other antecedents exhibit diverse effects within these groups. Regarding proposition P0, our findings support the presence of heterogeneous groups within the model. We have identified three distinct groups based on family composition and age. The first group, N1, encompasses individuals with either no children or more than one child. The second group, N2, consists of young individuals aged between 18 and 30 with a single child. The third group, N3, comprises adults aged 31 to 79 with a single child. Significant disparities are evident in the effects of two antecedents on online purchase intention among these three groups. In N1 and N3, the impact of attitude is nearly double that observed in N2. Conversely, the influence of SN in N3 is roughly three times greater than in N1.

Table 7 PLS-MGA results

Path / Test	Path differences/p-value		
	N1-N2	N1- N3	N2- N3
AT ->OPI	0.29	0.09	−0.20
PLS-MGA	0.00	0.23	0.03
Parametric Test	0.00	0.18	0.07
Welch-Satterthwait Test	0.00	0.23	0.03
PC->OPI	−0.10	0.10	0.20
PLS-MGA	0.26	0.11	0.06
Parametric Test	0.18	0.08	0.06
Welch-Satterthwait Test	0.27	0.12	0.06
SN ->OPI	−0.12	−0.19	−0.07
PLS-MGA	0.08	0.00	0.43
Parametric Test	0.08	0.00	0.48
Welch-Satterthwait Test	0.08	0.00	0.43
PT ->OPI	−0.05	0.01	0.07
PLS-MGA	0.39	0.75	0.33
Parametric Test	0.38	0.74	0.33
Welch-Satterthwait Test	0.38	0.74	0.33

5 CONCLUSION AND IMPLICATIONS

The study underscores marketers' need to tailor strategies based on demographic-specific online shopping behaviors in emerging markets. Attitude, perceived control, subjective norms, and perceived trust are crucial, but their impact varies by consumer segment. Recognizing these distinctions can enhance customer targeting and improve e-commerce engagement strategies.

The Pathmox algorithm emerges as a valuable tool for addressing heterogeneity in the e-commerce context. This highlights the suitability of advanced data science methodologies for understanding the complex dynamics of social behavior. Our findings refute the assumption that a simple linear relationship exists between external factors and e-commerce acceptance. This assumption overlooks the complex and dynamic interactions between multiple elements contributing to e-commerce behavior. Rather than assuming a direct, unidirectional effect, the results emphasize the importance of considering various influences, such as consumer demographics and cultural differences. This shift suggests that a more nuanced approach is necessary to understand e-commerce trends and develop strategies for the intricate interplay of various consumer behavior forces.

While the Pathmox algorithm provides valuable insights, it is imperative to acknowledge its limitations and delineate its application areas more clearly. Firstly, its effectiveness heavily depends on the quality and quantity of available data. Limited or biased datasets could impede its ability to capture heterogeneity accurately. Additionally, the algorithm's complexity may pose challenges for interpretation and implementation, especially for non-technical users. Furthermore, its applicability may vary across different contexts and industries, necessitating careful consideration of specific research questions. Lastly, although Pathmox with PLS-MGA offers a robust framework for understanding behavior heterogeneity, its utility may be constrained by factors such as sample representativeness and model assumptions, including the linearity of relationships and the assumption of causality associated with variance.

This study contributes to the existing body of knowledge in three keyways. First, it validates the Theory of Planned Behavior for e-commerce customer behavior in an emerging economy, confirming the theory's relevance in this setting. Second, by adding trust as an additional variable to the model, the study deepens our understanding of online purchase intentions, offering insights into consumer behavior in emerging markets. Third, it identifies distinct segments of online shoppers with statistically significant behavioral differences using a data science algorithm, which aids in segmenting and targeting these groups more effectively. The practical applications of these contributions are multifaceted. The Theory of Planned Behavior validation gives marketers and business leaders a solid framework for crafting targeted strategies in emerging economies. Incorporating trust into the explanatory model sheds light on how consumers in these markets make online purchasing decisions, emphasizing the need to build customer trust. Identifying unique consumer segments with varying motivations and behaviors allows companies to tailor their marketing strategies and customer experiences, leading to more personalized and effective campaigns.

The limitations of this study are primarily twofold. First, the cross-sectional method does not allow for determining changes in the relationships studied over time. Second, the study is limited by the non-random sample. Although it is a large sample of customers, the results of this study cannot be extrapolated to the entire population.

Future research could delve into longitudinal studies to track the evolving dynamics of segments within online consumer behavior over time, providing a deeper understanding of the development of purchasing patterns. Moreover, diversifying samples across various emerging economies would enhance insights into cultural distinctions that influence segmentation in online purchasing decisions. Furthermore, investigating specific e-commerce sectors, such as grocery shopping or online banking, using this segmentation methodology could be highly beneficial for practical purposes.

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