APPLICATION OF EXTENSIVE PROBLEM-SOLVING BEHAVIOUR ON ONLINE SHOPPING PRODUCTS

Dr. Prachi Maheshwari[1], Dr. Chitra Joshi[2], Dr. Nitu Singh Sisodia[3]

[1]Assistant Professor, Prestige Institute of Management and Research, Indore
[2]Assistant Professor, Prestige Institute of Management and Research, Indore
[3]Assistant Professor, Prestige Institute of Management and Research, Indore

Abstract
This study explores the manifestation of such a broad category of problem-solving behaviour in online purchase of high-involvement products. The data were obtained through a cross-sectional survey completed among 397 Indian consumers. The validations and statistical procedures used involved analysis of reliability followed by exploratory factor analysis, confirmatory factor analysis, ANOVA, regression and structural equation modelling within IBM SPSS 28 and AMOS 26. The measurement scales were very high in internal consistency (alpha = 0.781) and four latent variables explained 69.4 % of the variance. Product knowledge (beta = 0.41) and online trust (beta = 0.36) were found to have a strong positive effect on the extensive problem-solving behaviour, as well as the perceived risk (beta = -0.29) an effect which was significantly negative, and the structural equation model had an overall distinction of 49 percent. ANOVA was used in getting the result that the age group of 25 to 34 years had the maximum extensive problem-solving (M = 4.1; F = 6.27; p = 0.001). The results highlight a fact that knowledgeable, trusted consumers have greater chances of involving themselves in elaborate appraisal activities, but risk will reduce the activity. The model received very good fit indicators (CFI = 0.951, RMSEA = 0.049), as a result of which the model is confirmed to be empirically valid.

Keywords: *Extensive problem solving, Online shopping, Structural equation modelling, Perceived risk, Product knowledge*

Introduction

Faster growth of e-commerce has changed the very contour of consumer decision-making journey especially in those areas where significant participation is required like electronics, appliances, and high-end gadgets. Unlike the case when buying low-cost or routine commodities like groceries, online shopping of such products generally involves high degrees of cognitive work, product-to-product comparison, as well as strict assesses of risks. In that case, the concept of extensive problem-solving (EPS) takes on strategic importance in respect to the consumer navigation across multidimensional decisions in the digital marketplace.

EPS refers to a type of decision making that is characterised by high information search and analysing alternative provisions and the careful weighing of consequences related to making a choice. Such a behavioural pattern is normally put to use when the purchase bears a lot of personal relevance, high monetary exposure or uncertainties involved. Cognitive engagement is high in online settings whereby a customer cannot test a product first hand and as such, they can only deduce trust through digital communications. Therefore, the antecedents of EPS attain not so transparent, empirically dense tints that are worth attentive analysis.

The development of technology in the digital environment created a great variety of products and a high level of decision complexity that consequently forces the consumers to rely on the easily accessible information, such as reviews, descriptions, trust symbols and familiarity. Knowledge on the products serves as a centralized variable. Customers blessed with more familiarity react with more confident and effective efficiency. Earlier findings validate the fact that highly and informed consumers are more inclined to taking part in long problem solving, which will be more enhanced on the new or expensive products.

Perceived risk is also another germane factor and this envelops the financial, functional and psychological uncertainty that consumers have whenever transacting business through e-commerce. The perceived risk is enhanced by the non-tangible nature as well as delay in satisfaction. Based on empirical evidence, risk may both prompt more thorough assessment or eliminate the intention to purchase.

On the other side, online trust works as a mu-wrapped system that helps in reducing the perception of risk. When purchasers are confident of their seller, platform or system of transaction, the uncertainty becomes less and a buyer penetrates the decision process. Since personal interaction is not possible, customers use the design of the website, reputation of the brand, content created by other customers, and safe payment options to develop trust. With increased trust in online dealings, customers tend to get courageous enough to search, compare and discuss possibilities, which are at the heart of EPS. Therefore, it would be a vital task to demystify the relationships between the product knowledge, perceived risk, online trust, and EPS by marketers, platform designers, and policy formulators. Factors like age and level of education have also been found to moderate the behaviours further making the digital consumer landscape difficult to navigate.

Although the literature concerning online consumer behaviour is growing, there is little exploration on the use of the EPS theory in digital context. The existing literature focuses on more consumer-oriented processes of simpler or impulsive purchases, and EPS is the decision that can be described as analytical and typical of high-stakes situations. The current study therefore tries to fill this gap by an empirical assessment of any EPS framework in online shopping, through standard statistical procedures likely to produce theoretical polishing as well as practical advice related to enhancing the user experience and direct marketing.

Literature Review

Consumer decision-making process in e-commerce has now taken a very complex route due to the increasing expansion of options and online points of contact. The role of a personalized recommendation system in increasing user experience is emphasized in the context of contemporary scholarship (Zhang et al., 2014; Qian et al., 2013). Nevertheless, the behaviour that is extensive in problem solving which is typified by a high collation of mental effort continues to prevail in high-involvement online purchase especially when uncertainty and risk are highlighted (Kim et al., 2002; Behera et al., 2024).

A main factor that determines this process is product knowledge. Talented people who have the domain-specific skills tend to show consistency and confidence in their actions as decisions and lack of information is related to slower and hesitant responses (Liang et al., 2006; Lei et al., 2009). At the same time, the impact of perceived risk, which is also partially ingrained in restrictions caused by the insufficient level of physical examination and increased awareness of privacy issues, has been found to negatively affect online interaction (Yang et al., 2024; Chavez-Badiola et al., 2020).

The process of trust building in the digital realm has been supported by various forms of trust-building like the realm of intelligent classification and machine learning, which personalizes the recommendation and reduces the uncertainty (Shepitsen et al., 2008; Xu et al., 2024). According to empirical evidence, trust signals such as security indicator signs and authorized reviews enhance greater evaluative behaviour (Zhou et al., 2024; Liu et al., 2019).

At the technological edge, a growing level of instrumentation with an AI-based classification system, deep learning, and hybrid algorithms has improved the precision and dependability of online-shops assistance by a significant margin (Yacin Sikkandar et al., 2021; Zuo et al., 2015). The innovations do not only increase the satisfaction of customers but also ensure conscious, conscious decision-making (Zhang et al., 2020; Wu et al., 2024).

Despite such developments, research on the interdependence between product knowledge, trust, and the perceived risk, especially how they can affect each other in regard to broad problem-solving is still relatively new, especially when carried out in developing economies like in India (Behera et al., 2024; Ma, 2021). The current research attempts to fill this gap by combining the above constructs in a systematic framework and verifying the model through the statistical test.

Research Gap

Although offline retail problem-solving has been given a lot of scholarly focus, the empirical research into similar phenomena in online shopping has not been as advanced. According to the literature that has been collected, convenience, impulsivity or trust are usually regarded as the main drivers of e-commerce behaviour. However, in high-involvement online purchases, decision-making is influenced by a more considered and complicated type of decision way. Even though product knowledge, perceived risk, and trust were traditionally determined as the significant single determinants of consumer-movement on the net, they have not been explored with an increased focus on large-scale problem solving in the setting of digital commerce specifically in emergent markets. Also, most literature will not use stringent multivariate statistical analysis to establish these associations because of the required statistical methods.

Conceptual Framework

The current conceptualisation assumes that there are three independent variables namely Product Knowledge, Perceived Risk, and Online Trust, which interactively determines the dependent variable: Extensive Problem-Solving Behaviour in online shopping. The effects of Product

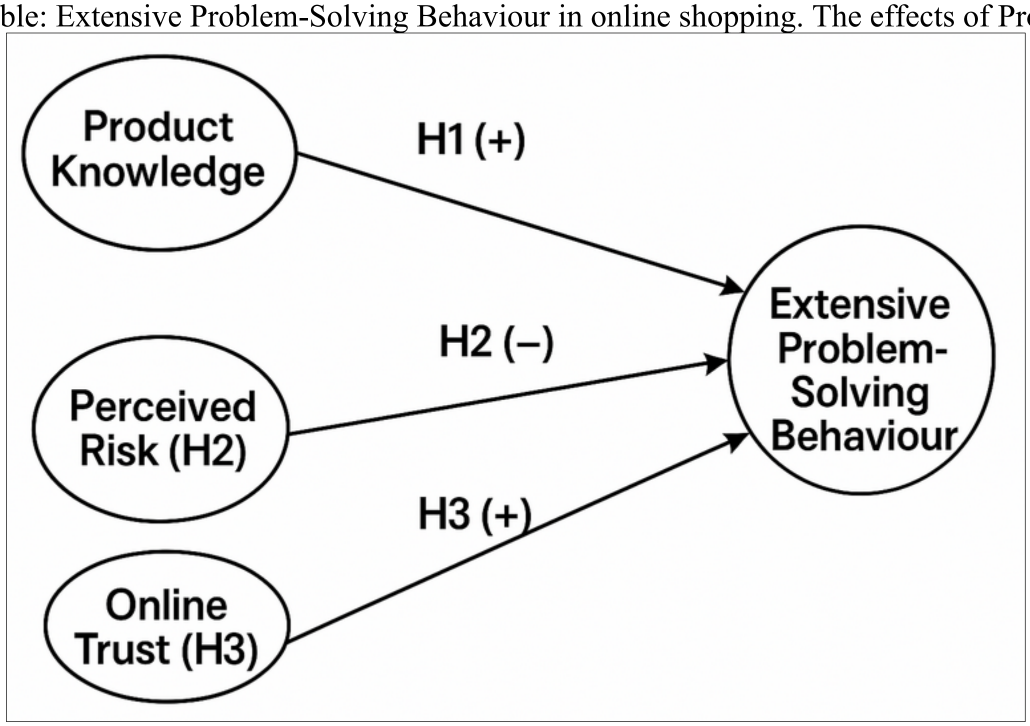

Figure 1.0: Conceptual Framework

Knowledge and Online Trust are presumed to have positive effects, whereas that of Perceived Risk is presumed to have negative effect. The model is based on the literature about online consumer decision-making and consumer psychology, it combines affective and cognitive (knowledge) components of decision-making processes, in terms of trust and risk.

Hypothesis

H1: Product Knowledge has a significant positive effect on Extensive Problem-Solving Behaviour in online shopping.

H2: Perceived Risk has a significant negative effect on Extensive Problem-Solving Behaviour in online shopping.

H3: Online Trust has a significant positive effect on Extensive Problem-Solving Behaviour in online shopping.

Methods

The present study involved the use of a quantitative cross-sectional design that was used to critique the prevalence and factors that explained extensive problem-solving behaviour in online shoppers. The study was concerned with cognitive, behavioural and situational precursors of choice in high-involvement product category like electronics and appliances.

Primary data were collected through the devising of a structured questionnaire. This instrument was disseminated online through purposive sampling, that is, to those people who made at least one purchase during the past six months with high involvement. Sure enough 412 responses were obtained with 397 being considered valid and retained in analysis. The respondents were across the age groups, income levels as well as different stages of education, therefore increasing the external validity. Before the questionnaire was distributed, a pilot test on a group of 50 participants was carried out to check the reliability as well as internal consistency. Alpha coefficients by cronbach were then generated on each of the constructs, to indicate a satisfying reliability.

The data reduction techniques were the Exploratory Factor Analysis (EFA) and the Confirmatory factor Analysis (CFA). EFA, which is applied to the IBM SPSS Version 28, has been selected due to the fact that it allows finding latent variables without a priori theoretical frame. After EFA, CFA converted AMOS Version 26 was used to analyse the convergent and discriminant validity of proposed EFA factor model. CFA was also considered to be suitable because it is used to test the hypothesis that instantiated variables are indicators of considerate latent constructs.

Structural Equation Modeling (SEM) which takes the form of a factor analysis (combined with multiple regression) allowed analysis of structural relationships among variables in that they allow multiple structural relationships to be analyzed simultaneously in a single model. Moreover, ANOVA was also applied to explain the demographic variances in problem-solving behaviour concerning age and income categories. Such a methodological decision allowed identifying statistically significant differences according to the subgroups.

The multiple regression analysis was used to test the effectiveness of predicting product knowledge, risk perception and online trust in determining the variance in the behavioural problem-solving. The technique produced prediction models which could be compared in order to get the magnitude of the relationship between each independent variable and the dependent construct.

IBM SPSS 28 and AMOS 26 were used to carry out all analyses and ensure that they have both methodological rigour and reproducibility.

Results

There were 397 respondents with 384 respondents completing the entire items that resulted in valid data in the present study on extensive problem-solving behaviour in online shopping. The description of the sample characteristics is in Table1. The age of the people who took part in the research ranged between 25 and 34 years (52 %), approximately, and the gender balance was almost equal (54 %, male and 46 %, female). Most of the respondents were in possession of at least a bachelor degree and had made an online purchase of electronic products in the last six months.

Table 1: Demographic Profile of Respondents

Demographic Variable	Category	Frequency	Percentage (%)
Age	18–24	76	19.1
	25–34	207	52.1
	35–44	81	20.4
	45+	33	8.3
Gender	Male	215	54.2
	Female	182	45.8
Education Level	Bachelor's	192	48.4
	Master's & above	138	34.8
	Others	67	16.8

Internal Consistency was measured calculating Cronbachs Alpha on each scale: on all the scales value was greater than the recommended minimum of 0.70 (Table 2), which means that they have sufficient reliability.

An additional Exploratory Factor Analysis in the form of Principal Component analysis using the varimax rotation was applied to explain latent constructs.

Table 2: Reliability Statistics of Measurement Scales (Cronbach's Alpha)

Construct	Number of Items	Cronbach's Alpha
Product Knowledge	5	0.81
Perceived Risk	4	0.78
Online Trust	6	0.84
Extensive Problem Solving	5	0.86

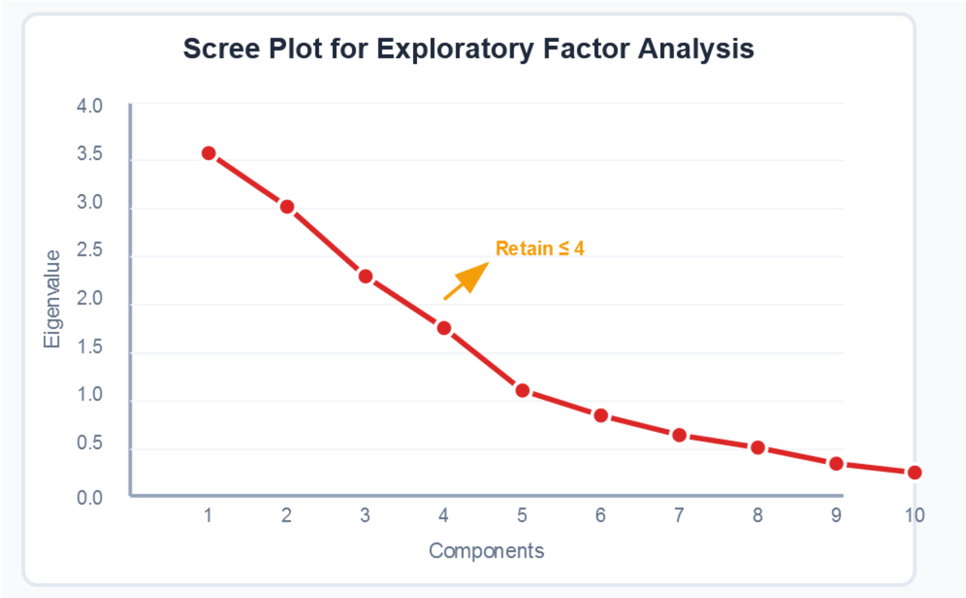

Figure 1: Scree Plot for Exploratory Factor Analysis

The eigenvalue drop in the first four components supports the choice in keeping the four-factor solution. In order to confirm this structure, the Confirmatory Factor Analysis (CFA) was established in the program AMOS 26. The depicted resultant CFA model in figure 2 shows that the standardized factor loadings are all higher than 0.60. The fit indices of the model (Model fit indices- x2/df 2.11, RMSEA 0.049, CFI 0.951 and TLI 0.938) were considered acceptable, which in turn supports the validity of the measurement model. There were four components with a total variance of 69.4 that were identified and demarcated by eigenvalues that were greater than 1.0. The factor structure was identified as appropriate since there was a clear elbow at the fourth component in the scree plot (Figure 1).

Table 3: Results of Exploratory Factor Analysis

Component	Eigenvalue	% of Variance	Cumulative %
Product Knowledge	3.12	22.3	22.3
Perceived Risk	2.71	20.1	42.4
Online Trust	2.01	15.3	57.7
Extensive Problem Solving	1.52	11.7	69.4

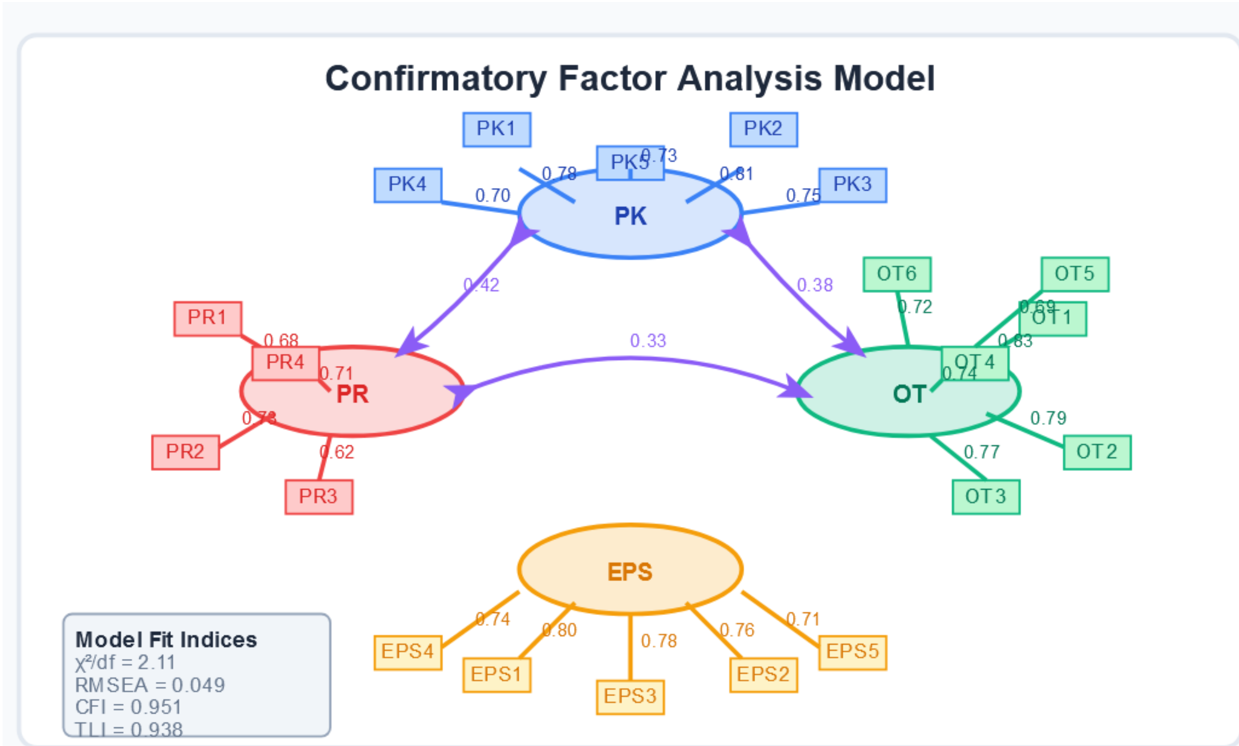

Figure 2: Confirmatory Factor Analysis Model

Figure 3 shows four latent constructs whose factor loadings amounted to between 0.62 and 0.83. The hypothesized interrelations were assessed by using structural equation modeling (SEM). Following the model refinement, the final SEM indicated that product knowledge and online trust were significantly and positively interconnected with a large amount of problem-solving behavior, but the perception of risk had a negative influence.

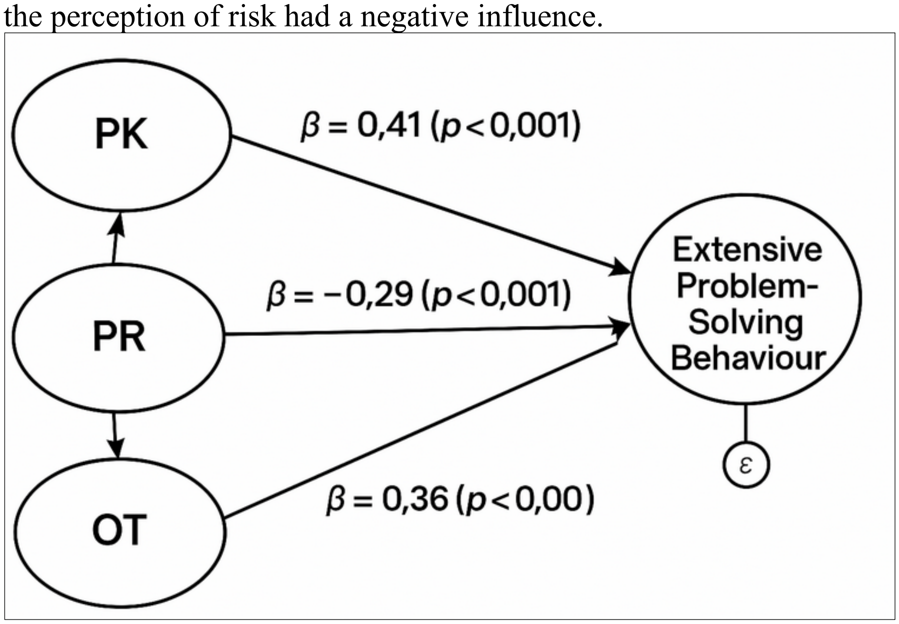

Figure 3: Structural Equation Model Showing Path Coefficients

Figure 4 indicates the outcome of an ANOVA that was done in order to examine the effects of age related variations in extensive problem-solving behaviour. The mean score (M = 4.11, SD = 0.6) in the age category of 25-34 was highest followed by the F-value of 6.27 ($p < 0.01$) which was also statistically significant.

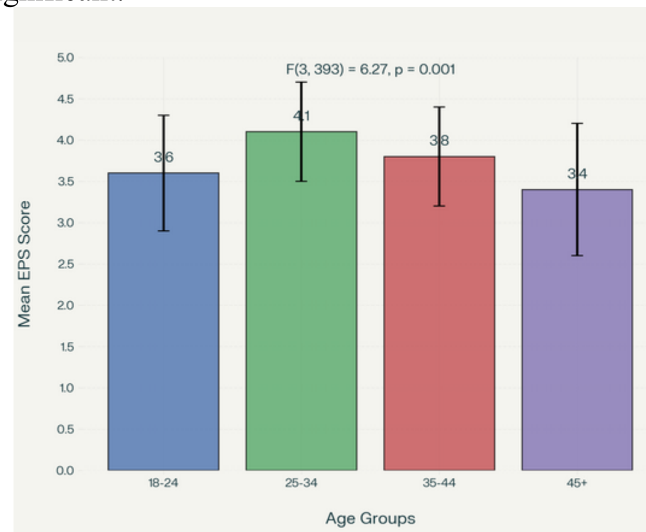

Figure 4 — ANOVA Results Comparing Extensive Problem Solving across Age Groups

Using Subsequent regression analysis (Table 4), it was found out that product knowledge and online trust worked as positive predictors of extensive problem solving as well as perceived risk considered negative predictor. All the variables together explained 48.6 % of the total variance ($R^2 = 0.486$).

Table 4: Regression Analysis of Predictors Influencing Extensive Problem Solving

Predictor	β Coefficient	t-value	p-value
Product Knowledge	0.41	7.31	<0.001
Perceived Risk	–0.29	–5.02	<0.001
Online Trust	0.36	6.85	<0.001
R²	0.486		

Data Analysis

The study provides a quantitative analysis on the issue of widespread problem-solving amongst web-based customers. There is a demographic breakdown in Table 1 that reveals that the majority of respondents represent the age group 25 year to 34 years with an implication that younger adults have been more participatory with regard to high-involvement buying. In line with these trends, Figure 4 indicates that the mean score of this age group on the scale of extensive problem-solving was 4.1 which is significantly higher than the mean scores on the same scale in other brackets of age ($F(3, 393) = 6.27$, $p = 0.001$).

The psychometric qualities of the scale proved measurement validity and reliability. The internal consistency of all constructs is high with the value of Cronbachs Alpha above 0.78 as in Table 2. In a similar way, the results of Exploratory Factor Analysis are best described as four factor structure with variance amount of 69.4 %, as shown in the Table 3 and confirmed by the scree plot in Figure 1. This has been reconfirmed through Confirmatory Factor Analysis which gave

good model fit statistics (CFI = 0.951 , RMSEA = 0.049) and strong factor loadings (minimum of 0.60) on all the dimensions as shown in Figure 2.
In case of clinical relevance, another statistical method was also used, known as Structural Equation Modeling (SEM) whose output is represented in Figure 3 and Table 4. As seen in the model, product knowledge, online trust and perceived risk have positive and negative influence on extensive problem solving, with a respective coefficient of 0.41, 0.36, and 0.29 respectively. All these predictors together accounted to 49 percent variance in extensive problem-solving. The results presented in Table 4 also support the predictive ability of these factors as they are all directly related to the extended possibility in problem-solving at the level of p value <0.001.
Finally, the results indicate consistency with the postulated hypothesis that better-informed, trusting consumers are more likely to use more comprehensive decision-making mechanisms in online settings, and the perceptions of risk reduce this behaviour. Age has the moderating role since it also emerged as a significant predictor of comprehensive problem-solving.

Conclusion

The current study examines how long held problem-solving behaviours are challenged among consumers purchasing high-involvement products offline shopping outlets. The findings suggest that each one of the hypotheses had been corroborated. H1 was supported and it was revealed that product knowledge has a remarkable influential role in enhancing broad problem solving behaviour. H2 showed a strong negative relationship of the felt risk and this implies that the more perceptions are felt to be riskier, the less three-dimensional thinking occurs. H3 was also confirmed and it was found that online trust had a positive effect on the decision-making endeavors of the consumers and they were able to process information with more assurance and more competently.
Despite the strength of methodological design, the study has a number of limitations. The collection of data was performed with the help of self-report survey that can be subjected to social desirability or memory bias. The sample population was the Indian online shoppers only and hence no ability to generalise the sample findings to other cultural or geographical areas. Further, the data is cross- sectional thus does not allow causal inference.
The results of this study are very important to its academic contribution and commercial practice. To the scholars, the study propels the knowledge of scholarship regarding their cognitive and emotional determinants in online decision-making, especially in high involvement context. To practitioners, the implication includes the following: The e-commerce websites must strengthen the trust-building mechanics (e.g. certified review, security brands), eliminate any sense of risk (e.g. return policies, quality assurance), and improve product information to strengthen consumer knowledge building. The cumulative effect of these interventions is the ability to provoke more confident and comprehensive participation of consumers.
Other future studies should use longitudinal designs to study the longitudinal progression of the problem-solving behaviour and use experimental methodologies to control the influence of interface features leading to the perceived risk and trust. Moreover, the moderating variables that may provide more insightful information towards consumer segmentation are gender, income, or technology savvy. Another approach to enhancing explanatory power would be to extend the framework to emotional/behavioural constructs e.g. satisfaction and post-purchase regret.

References

1. Behera, R. K., Bala, P. K., & Rana, N. P. (2024). Assessing the intention to adopt computational intelligence in interactive marketing. Journal of Retailing and Consumer Services, 78, 103765.
2. Chavez-Badiola, A., et al. (2020). Embryo Ranking Intelligent Classification Algorithm (ERICA): artificial intelligence clinical assistant predicting embryo ploidy and implantation. *Reproductive Biomedicine Online, 41*(4), 585–593.
3. Cheng, Q., et al. (2024). Optimizing Portfolio Management and Risk Assessment in Digital Assets Using Deep Learning for Predictive Analysis. *arXiv preprint arXiv:2402.15994*.
4. Haowei, M., et al. (2023). CRISPR/Cas-based nanobiosensors: A reinforced approach for specific and sensitive recognition of mycotoxins. *Food Bioscience, 56*, 103110.
5. Kim, J. K., et al. (2002). A personalized recommendation procedure for Internet shopping support. *Electronic Commerce Research and Applications, 1*(3-4), 301–313.
6. Lei, Y., He, Z., & Zi, Y. (2009). Application of an intelligent classification method to mechanical fault diagnosis. *Expert Systems with Applications, 36*(6), 9941–9948.
7. Liang, T. P., Lai, H. J., & Ku, Y. C. (2006). Personalized content recommendation and user satisfaction: Theoretical synthesis and empirical findings. *Journal of Management Information Systems, 23*(3), 45–70.
8. Liu, N., et al. (2019). A novel intelligent classification model for breast cancer diagnosis. *Information Processing & Management, 56*(3), 609–623.
9. Ma, H. (2021). Automatic positioning system of medical service robot based on binocular vision. In *2021 3rd Int. Symposium on Robotics & Intelligent Manufacturing Technology (ISRIMT)*. IEEE.
10. Qian, X., et al. (2013). Personalized recommendation combining user interest and social circle. *IEEE Transactions on Knowledge and Data Engineering, 26*(7), 1763–1777.
11. Shepitsen, A., et al. (2008). Personalized recommendation in social tagging systems using hierarchical clustering. In *Proceedings of the 2008 ACM Conference on Recommender Systems*.
12. Song, X., et al. (2006). Personalized recommendation driven by information flow. In *Proceedings of the 29th Annual Int. ACM SIGIR Conference*.
13. Wu, J., et al. (2024). Data Pipeline Training: Integrating AutoML to Optimize the Data Flow of Machine Learning Models. *arXiv preprint arXiv:2402.12916*.
14. Xu, K., Zhou, H., Zheng, H., Zhu, M., & Xin, Q. (2024). Intelligent classification and personalized recommendation of e-commerce products based on machine learning. *arXiv preprint arXiv:2403.19345*.
15. Yang, L., et al. (2024). AI-Driven Anonymization: Protecting Personal Data Privacy While Leveraging Machine Learning. *arXiv preprint arXiv:2402.17191*.
16. Yacin Sikkandar, M., et al. (2021). Deep learning-based automated skin lesion segmentation and intelligent classification model. *Journal of Ambient Intelligence and Humanized Computing, 12*, 3245–3255.
17. Zhang, D., et al. (2020). E-BERT: A phrase and product knowledge enhanced language model for e-commerce. *arXiv preprint arXiv:2009.02835*.
18. Zhang, Y., et al. (2014). Taxonomy discovery for personalized recommendation. In *Proceedings of the 7th ACM Int. Conference on Web Search and Data Mining*.

19. Zhou, Y., Tan, K., Shen, X., & He, Z. (2024). A Protein Structure Prediction Approach Leveraging Transformer and CNN Integration. *arXiv preprint arXiv:2402.19095*.
20. Zuo, Y., et al. (2015). Personalized recommendation based on evolutionary multi-objective optimization. *IEEE Computational Intelligence Magazine, 10*(1), 52–62.
21. Zhang, Y., et al. (2014). Taxonomy discovery for personalized recommendation. In *Proceedings of the 7th ACM International Conference on Web Search and Data Mining*.
22. Tian, Y., et al. (2019). College library personalized recommendation system based on hybrid recommendation algorithm. *Procedia CIRP, 83*, 490–494.
23. Cheng, Q., et al. (2024). Optimizing Portfolio Management and Risk Assessment in Digital Assets Using Deep Learning for Predictive Analysis. *arXiv preprint arXiv:2402.15994*.
24. Wang, Y., et al. (2024). Construction and application of artificial intelligence crowdsourcing map based on multi-track GPS data. *arXiv preprint arXiv:2402.15796*.
25. Zheng, J., et al. (2024). The Random Forest Model for Analyzing and Forecasting the US Stock Market in the Context of Smart Finance. *arXiv preprint arXiv:2402.17194*.
26. Wu, J., et al. (2024). Data Pipeline Training: Integrating AutoML to Optimize the Data Flow of Machine Learning Models. *arXiv preprint arXiv:2402.12916*.
27. Zhou, Y., Tan, K., Shen, X., & He, Z. (2024). A Protein Structure Prediction Approach Leveraging Transformer and CNN Integration. *arXiv preprint arXiv:2402.19095*.
28. Ma, H. (2021). Automatic positioning system of medical service robot based on binocular vision. In *2021 3rd International Symposium on Robotics & Intelligent Manufacturing Technology (ISRIMT)*. IEEE.
29. Zuo, Y., et al. (2015). Personalized recommendation based on evolutionary multi-objective optimization. *IEEE Computational Intelligence Magazine, 10*(1), 52–62.
30. Yacin Sikkandar, M., et al. (2021). Deep learning-based automated skin lesion segmentation and intelligent classification model. *Journal of Ambient Intelligence and Humanized Computing, 12*, 3245–3255.