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Machine Learning-Driven Prediction of Consumers' Pre-purchase Safety Behaviors in Online Shopping Malls

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As online shopping malls play an increasingly crucial role in consumers' daily lives, large amounts of consumer and transactional data have become available. While current machine learning applications in e-commerce focus primarily on enhancing customer experience, increasing sales, and providing personalized recommendations, the analysis of consumer risk behaviors remains underexplored. This study addresses that gap by predicting consumers' pre-purchase safety behaviors to enable the development of personalized safety education programs, ultimately helping prevent unsafe or non-compliant product purchases. We utilize an online survey dataset, which includes consumer demographics, newly defined safety knowledge levels, and reported safety practices—such as checking reviews, monitoring public alerts, and verifying sellers. Five machine learning models were compared: Linear Regression, Random Forest, Neural Network, XGBoost, and SVM. Results from the model comparison indicate that SVM outperforms the other methods, achieving the lowest mean absolute error in numerical predictions and the highest accuracy and AUC in binary classifications of safety behaviors. These findings highlight the influential role of consumer safety knowledge and demographics in shaping pre-purchase risk decisions. Based on the SVM model's predictions, we propose personalized consumer safety education initiatives, such as pre-purchase pop-up or e-mails, that online mall operators can implement to promote safer purchasing decisions. The study demonstrates the feasibility and effectiveness of machine learning in identifying high-risk consumers, offering valuable insights for enhancing product safety awareness and fostering safer e-commerce environments.

Keywords: Online Shopping Malls, Consumer Knowledge, Consumer Education, Pre-Purchase Behaviors, Product Safety, Machine Learning, Risk Mitigation, Predictive Analytics, Personalized Interventions, Cross-Border E-commerce, Data Privacy, Internet Consumer Behavior.

1. Introduction

In recent years, the Business-to-Consumer (B2C) e-commerce market has rapidly expanded. According to reports by the Ministry of Economy, Trade and Industry (METI) in Japan, the B2C e-commerce market reached over 24.8 trillion JPY by 2023 (METI 2024). Today, consumers can purchase a wide variety of products online, ranging from food and pharmaceuticals to apparel products. Simultaneously, however, product-related safety incidents sourced from internet transactions have significantly increased, with serious safety incidents linked to items such as lithium-ion batteries sold online surging. As of 2023, approximately 26.7% of reported serious product safety incidents can be traced to products purchased through internet shopping channels (METI 2023). The rise in overseas sellers, cross-border transactions, and third-party sellers further complicates product safety assurance in E-commerce.

Consequently, online shopping malls, which serve as large-scale virtual marketplaces consolidating numerous sellers and products, are increasingly recognized as key players in enhancing product safety and consumer protection. Policy initiatives such as the Japan

Product Safety Pledge (2023) and the OECD statement have prompted marketplace platformers to commit to voluntary product safety commitments. Concurrently in Japan, from 2024 onwards, enhanced regulations and amendments to the Four Product Safety Acts are strengthening oversight on products sold online, particularly children's products and cross-border sales.

In addition to policy and industry measures, recent regulatory recommendations emphasize the importance of consumers' proactive role—consumers should actively seek information on product safety from initiatives by the government and mall operators, and use this as a basis for evaluating product safety, and choose products that are safer before a purchase (METI 2020). However, consumer safety behavior research in the context of online marketplaces remains limited, particularly concerning their knowledge of safety measures and pre-purchase risk assessment behaviors.

On the other hand, some malls have launched pioneering efforts to harness consumer data for personalized safety education. For instance, Amazon's "Anshin Mail" service proactively delivers product safety information to customers based on their demographic and purchase information, demonstrating the potential for large-scale e-commerce platforms to implement targeted safety alerts (Amazon.com 2024; Miura 2022). However, it predominantly focuses on post-purchase education, meaning consumers receive vital safety information only after completing a transaction, rather than beforehand.

Despite the rise of "E-commerce-led safety" initiatives, two key challenges persist in advancing consumer safety research within online marketplaces. First, existing literature lacks a widely accepted definition or framework for "safety knowledge" or "pre-purchase safety behaviors" specific to online shopping environments. This gap makes it difficult to apply established models or measures, necessitating the development of new survey items and operational definitions based on previous research and public safety warnings. Second, while consumer behavior in e-commerce has been extensively studied in terms of satisfaction and purchase intentions, research on how consumers proactively ensure product safety (e.g., verifying seller credibility, safety marks, and public alerts) remains limited.

This study seeks to address these gaps. Building on earlier work that surveyed consumers' knowledge and pre-purchase safety behaviors in online malls, we now integrate machine learning-based predictive modelling to forecast consumers' likelihood of engaging in risk-mitigating actions. By applying Linear Regression, support vector machines (SVM), random forest, Neural Network, and XGBoost models, this research identifies the key predictors of consumer risk levels. Ultimately, this approach supports the development of personalized consumer education programs and policy interventions that cater to consumers' existing knowledge and practices, thereby fostering safer online shopping environments.

Hence, the objectives of this research are:

- To investigate how consumer demographics and safety knowledge correlate with pre-purchase risk behavior.
- To develop machine learning models to identify key predictive factors for consumer risk levels.
- To provide actionable insights to marketplace operators and policymakers for enhancing consumer safety awareness and platform safety features.

2. Literature Review

Existing research on consumer behavior in online shopping environments has largely focused on marketing and trust-building mechanisms. Past studies emphasize convenience, perceived risk, trust, and information security in shaping purchase intentions. However, there were fewer studies in product safety awareness and related pre-purchase behaviors, and thus do not fully address how to proactively educate consumers before they finalize transactions.

2.1. *Information search behavior*

Consumers often rely on product descriptions, seller ratings, and customer reviews. However, the reliability of reviews can be compromised by misinformation. Earlier studies, such as (BEIS, 2020), indicate that consumers may not fully recognize the risks of online purchases and tend to rely heavily on ratings and reviews without verifying their authenticity. Similarly, surveys by NSF (2019) reveal that while consumers express interest in product safety, they do not consistently engage in proactive safety checks before purchasing. These prior works do not explore how pre-purchase alerts or ML-driven prompts intervene at the point of transaction.

2.2. *Trust and perceived risk*

Trust in the marketplace and sellers influences consumer confidence. Levi et al. (2021) found that consumers who fail to search for safety information may be more likely to engage in unsafe purchasing behaviors. Ajzen's (1991) Theory of Planned Behavior also helps explain how perceived behavioral control and social norms shape intentions to perform safety checks, yet such theoretical frameworks generally stop short of proposing data-driven personalization methods. Therefore, while these theories highlight the importance of safety knowledge, they have not systematically applied machine learning to deliver targeted interventions before checkout.

2.3. *Consumer knowledge and awareness of online safety practices*

Past research in Japan and abroad (NSF 2019) suggests that knowledge about marketplace structures, overseas transactions, and recognized safety certifications (e.g., PS marks) is unevenly distributed among consumers. Certain consumer groups demonstrate higher awareness of online product safety, while others, particularly those less informed about product information, tend to exhibit lower levels of safety knowledge and cautious purchasing behaviors (Levi et al. 2021). Although regulators propose consumer alerts, prior studies lack a data-driven framework that predicts who is most at risk and needs these alerts.

2.4. *Impact of consumer education on online safety behaviors*

Recent initiatives propose consumer education as a strategy to enhance safety behavior online. For instance, JADMA and METI guidelines suggest that providing tutorials or alerts can improve consumer engagement with safety practices (CAA 2020; METI 2020; NITE 2021; JADMA 2020). However, these guidelines do not incorporate predictive modelling to identify specific consumers who might neglect safety actions. Additionally, data privacy regulations (e.g., GDPR) receive minimal coverage in these interventions, indicating a need for a responsible personalization approach.

2.5. *Machine learning for predicting consumer behavior*

Machine learning approaches have been widely used in e-commerce to predict satisfaction, churn, segment customers, and recommend products. However, the application of ML to forecast consumer pre-purchase safety behaviors remains nascent. Chaubey et al. demonstrates how various classification models (logistic regression, decision trees, KNN, SVM, random forest, AdaBoost, and XGBoost) can be evaluated for accuracy. Still, these works mostly emphasize broad consumer behavior outcomes rather than targeted, pre-purchase safety checks. Zaghloul et al. (2024) benchmarked traditional ML and deep learning models for e-commerce satisfaction predictions, showing random forest's strong performance (Zaghloul et al., 2024). Overall, these studies have not fully leveraged ML to produce real-time, pre-purchase alerts that might reduce unsafe or non-compliant buying.

A gap exists in applying ML-driven predictive modelling to pre-purchase consumer safety knowledge and educational interventions. While online shopping malls are well-studied from a marketing perspective, research on their role in product safety through data-driven consumer education remains limited. Integrating established consumer behavior theories, advanced interpretability methods, and recognition of privacy frameworks could yield more targeted, compliant educational strategies. Our research extends these studies by identifying key predictors of consumer pre-purchase safety behaviors and developing a machine learning-driven framework that informs users before purchasing risky products.

3. Research Methodology

3.1. *Data collection*

We conducted an online survey (N=500) targeting Japanese consumers who had shopped at least once in an online marketplace. The questionnaire covered demographics (age, gender, education), online shopping frequency, safety knowledge (awareness of marketplace structure, cross-border transactions, review authenticity, and safety marks), and 11 pre-purchase safety behaviors (checking product safety alerts, verifying safety marks, reading product review, etc.). A sample size of 50 was obtained for each age and gender group. After data cleaning, 266 valid records were obtained, representing a broad range of demographics.

Table 1. Main data features and encoding schemes

Label		Variable	Data
Consumer Attributes	Gender	Male	1
		Female	2
	Age	15-29 age	1
		30-39 age	2
		40-49 age	3
		50-59 age	4
		60-69 age	5
	Educational Background	Secondary Schools	1
		High School	2
		University (short-term)	3
		University (4-year)	4
		Graduate School	5
	Marital Status	Unmarried	1
		Married	2
Knowledge Level	Understanding the Mall Structure	Understand	1
		Not Understand	0
	Understanding Cross-border Trade	Understand	1
		Not Understand	0
	Understanding the Reviews Credibility	Understand	1
		Not Understand	0
	Understanding Safety Marks	PSE Mark	1/0
		PSC Mark	1/0
		PSLPG Mark	1/0
		PSTG Mark	1/0
		ST Mark	1/0
		SG Mark	1/0
		Don't know the above signs	1/0
Number of Safety Actions Prior to Purchase	Product Safety Confirmation Actions (6 actions)	#1: Check the presence or absence of safety standards and marks	1/0
		#2: Look up information about the safety of the product on websites other than Internet malls	1/0
		#3: Check to see if there are any recalls or incidents related to the product posted on public websites	1/0
		#4: Find information about product hazards on your product page	1/0
		#5: Check the product page for handling precautions	1/0
		#6: Check the country of origin, manufacturer, and seller	1/0
	Review Confirmation (2 Actions)	#7: Check the overall rating of a product review on the product page	1/0
		#8: Check the distribution of the number of product reviews and points on the product page	1/0
	Seller Confirmation (2 Actions)	#9: Check the merchant's reputation	1/0
		#10: Check after-sales measures such as sales compensation system	1/0
	Mall Confirmation (1 Action)	#11: Check if the online mall pre-screens your products	1/0

3.2. *Data preprocessing*

Responses were cleaned by removing incomplete cases and outliers (e.g., unrealistic response patterns). All categorical variables were encoded, and continuous variables were standardized or scaled. Table 1 summarizes the main data features and encodings. Preliminary analyses such as correlation checks and chi-square tests were conducted to examine feature relevance.

3.3. *Feature engineering*

Key features included:

- Consumer attributes (age, gender, education, marital status),
- Knowledge variables (e.g., understanding of marketplace operations, cross-border transaction risks, review credibility, safety marks), and
- Self-reported pre-purchase safety behaviors (e.g., verifying country of origin, checking safety marks, reading external product alerts).

We also computed:

- Knowledge level scores: Based on understanding of four core domains—marketplace structure, cross-border transaction risks, review credibility, and safety marks.
- Safety behavior scores: From an 11-item checklist (e.g., verifying country of origin, checking safety certificates, reading external product alerts).

3.4. *Machine learning models*

To predict consumers' pre-purchase safety behavior (specifically, the number of safety actions performed or the likelihood of performing each action), we selected five well-established machine learning models—Linear/Logistic Regression, Random Forest, Neural Network, XGBoost, and SVM—to systematically evaluate which approach best handles our relatively small yet feature-rich dataset.:

- Linear Regression and Logistic Regression (baseline models for numerical or binary classification).
- Random Forest (ensemble of decision trees).
- Neural Network (a single hidden-layer feed-forward architecture).
- XGBoost (Linear) (gradient-boosted linear model).
- Support Vector Machine (SVM) (kernel-based approach).

Hyperparameter tuning was performed via grid search and 5-fold cross-validation. Each model was assessed using training (80% of dataset) and testing (20% of dataset) partitions.

3.5. *Evaluation metrics*

We evaluated model performance via Mean Absolute Error (MAE) for numerical predictions (i.e., predicting the count of safety actions from 0 to 11). For classification tasks (i.e., whether a consumer will perform a particular action), we used accuracy, ROC curves, and AUC. We also monitored potential overfitting by comparing results on training and test subsets.

4. Results

4.1. *Descriptive statistics*

Preliminary descriptive statistics indicated that approximately 51.6% of respondents understood the difference between marketplace operators and sellers, while 57.2% recognized at least one product safety mark (PS, ST, or SG marks). Younger consumers (15 to 29 years) generally displayed lower knowledge levels than older counterparts. Marital status and online shopping frequency were also correlated with knowledge scores. Across the sample, the average number of safety behaviors performed before purchase was 2.75 out of 11.

4.2. *Relationships between variables*

Chi-square tests and correlation analyses revealed significant relationships between knowledge levels and certain demographic attributes. For instance, the younger the age group, the lower the average score and the ratio of high-knowledge level consumers, and the older the age group, the higher the ratio of high-knowledge level consumers.

4.3. *Extended model comparison and SVM performance*

4.3.1. *Comparison of multiple machine learning models*

To validate the predictive effectiveness of our approach, we compared five machine learning models in predicting the number of pre-purchase safety actions. The dataset (N=266) was split 80:20 for training and testing, and the same feature set was applied to each model. Table 2 shows the Mean Absolute Error (MAE) for each model on the training and test sets:

Table 2. Mean Absolute Errors for Each Model

Model	Train	Test
SVM	1.039	0.991
Random Forest	1.799	1.384
Neural Network	1.846	1.517
Linear Regression	1.787	1.322
XGBooost Linear	1.625	1.906

Support Vector Machine (SVM) achieved the lowest MAE on both training (1.039) and test (0.991) sets, indicating strong generalization and minimal overfitting.

Random Forest and Neural Network showed moderate errors, while Linear Regression and XGBoost (Linear) yielded higher overall MAEs, suggesting they may not capture the complexity of the data as effectively as SVM.

Based on these results, SVM was selected as the primary model for subsequent analyses.

4.3.2. *Numerical prediction analysis (SVM)*

Using SVM for numerical prediction, we examined additional error metrics. Table 3 summarizes the minimum/maximum error, average error, MAE, standard deviation, and correlation on both training and test sets.

Mean Absolute Error (MAE) remains below 1 for both training and test sets, supporting stable performance. Standard Deviation of errors is slightly lower in the test set, indicating consistent prediction.

Correlation of ~0.63 on the test set shows a moderate positive relationship between predicted and actual values, highlighting potential areas for further feature engineering.

Table 3. SVM Model Performance Metrics (Numerical Prediction)

Partition	Training	Testing
Minimum Error	-4.1	-3.59
Maximum Error	9.531	8.442
Average Error	0.359	0.244
Mean Absolute Error	1.039	0.991
Standard Deviation	1.887	1.823
Linear Correlation	0.642	0.629
Data	216	48

4.3.3. *Integrated classification prediction*

We also converted the safety action count (0–11) into multiple binary classification tasks, each focusing on whether or not a particular action was performed. Again, SVM was employed using an 80:20 train-test split, and Table 4 displays classification accuracy across all 11 pre-purchase safety actions.

Table 4. Classification Accuracy by Action (SVM)

Action	Train		Test	
	Correct	Error	Correct	Error
#1	179 (82.87%)	37 (17.13%)	40 (83.33%)	8 (16.67%)
#2	188 (87.04%)	28 (12.96%)	41 85.42%)	7 (14.58%)
#3	200 (92.59%)	16 (7.41%)	44 (91.67%)	4 (8.33%)
#4	197 (91.2%)	19 (8.8%)	43 (89.58%)	5 (10.42%)
#5	193 (89.35%)	23 (10.65%)	42 (87.5%)	6 (12.5%)
#6	171 (79.17%)	45 (20.83%)	40 (83.33%)	8 (16.67%)
#7	190 (87.96%)	26 (12.04%)	45 (93.75%)	3 (6.25%)
#8	176 (81.48%)	40 (18.52%)	39 (81.25%)	9 (18.75%)
#9	209 (96.76%)	7 (3.24%)	48 (100%)	0 (0%)
#10	188 (87.04%)	28 (12.96%)	42 (87.5%)	6 (12.5%)
#11	201 (93.06%)	15 (6.94%)	46 (95.83%)	2 (4.17%)

Overall classification accuracy is notably high in both training and test sets, reinforcing SVM's robustness. Some actions (e.g., Action#9) appear easier to classify, while others (e.g., Action#6, Action#8) show lower accuracy, suggesting potential areas for feature optimization.

4.3.4. *ROC, AUC, and Gini coefficients*

To further evaluate classification performance, we computed ROC curves and measured the Area Under the Curve (AUC) alongside the Gini coefficient for each action (binary classification). Table 5 shows the AUC and corresponding Gini values (where Gini = 2*AUC - 1) for both training and test sets.

Table 5. AUC and Gini Coefficients (SVM)

Action	Train		Test	
	AUC	Gini	AUC	Gini
#1	0.876	0.752	0.946	0.893
#2	0.910	0.820	0.787	0.574
#3	0.881	0.762	0.933	0.865
#4	0.920	0.841	0.891	0.781
#5	0.926	0.852	0.991	0.981
#6	0.890	0.781	0.938	0.875
#7	0.913	0.825	0.984	0.969
#8	0.915	0.830	0.889	0.778
#9	0.950	0.900	1.000	1.000
#10	0.921	0.843	0.947	0.893
#11	0.936	0.873	0.937	0.874

The table shows high AUC (≥ 0.85) in most cases indicates excellent discrimination. Action#9 attained a perfect 1.000 in the test set, suggesting an easily identifiable pattern (but caution is necessary due to smaller sample segments). Some actions (e.g., Action#2) exhibited lower test-set AUC compared to training, indicating a degree of overfitting. Nonetheless, overall performance remained strong.

5. Discussion

5.1. *Interpretation of findings*

Our results show that consumers with higher safety knowledge are more likely to perform pre-purchase safety actions. The SVM model's superior performance (lowest MAE in numerical prediction and high accuracy/AUC in classification tasks) underscores its suitability for modelling relatively small datasets and capturing complex interactions among demographic, knowledge, and behavioral variables. These findings align with prior literature (OECD 2016; Levi et al. 2021), illustrating that consumer knowledge and trust mechanisms significantly influence online safety behavior.

5.2. *Implications for each player*

The findings in this study deliver various implications for each player.

For Marketplace Operators: Our results highlight the potential for online marketplaces to serve as a centralized platform for targeted safety education. Because many consumers congregate in these large online malls today, personalized pop-ups, tutorials, or email alerts can efficiently reach high-risk users before and after they complete a purchase. This "hub" role is particularly critical, as traditional consumer education efforts, such as public alerts, may not reach individuals at the exact moment of decision-making. Through tailored interventions, operators can empower consumers by bridging specific knowledge gaps.

However, collecting and utilizing predictive data on consumer safety behaviors must be approached with ethical responsibility. If "low-safety-check user" information were to fall into the hands of fraudulent sellers or unauthorized third parties, these vulnerable segments could be specifically targeted with risky or counterfeit products. This risk highlights the need for robust data governance and user consent frameworks.

For Consumers: Enhanced consumer awareness is a key advantage of predictive approaches. By identifying which demographic segments have lower levels of safety knowledge, marketplace operators and policymakers can design targeted awareness campaigns that encourage consumers to perform safety checks more consistently. This can lead to fewer unsafe purchases and help users become more proactive about verifying seller credentials, checking safety marks, and monitoring public alerts. Over time, greater consumer engagement with safety measures could foster a cultural shift toward more responsible online shopping behaviors.

For Policymakers: Public authorities play a critical role in regulating data use and promoting ethical guidelines for predictive modelling. Policies that encourage or mandate transparency about product safety information can facilitate better consumer decision-making, especially if combined with data-driven predictive tools that alert consumers of potential risks in real-time.

5.3. *Limitations*

While the SVM model achieved strong performance, the study relies primarily on self-reported data and a single geographic region. A limitation of this study is the relatively small size of the data set, only 266 questionnaires, used for predicting the consumers' pre-purchase safety behaviors which resulted from the respondents from a single country (Japan) also limits generalizability. Further data collection from broader demographic and cross-border contexts could reveal more robust patterns.

6. Conclusion

This study bridges the gap between consumer safety knowledge research and machine learning-based predictive modelling in online marketplaces. By applying SVM and other classification models to consumer attributes, knowledge levels, and safety behaviors, we identified key predictors of pre-purchase risk and demonstrated the feasibility of accurately forecasting consumer safety actions. Among the tested models (Linear Regression, Random Forest, Neural Network, XGBoost, and SVM), SVM achieved the best predictive performance, highlighting its effectiveness for this particular dataset.

The findings suggest practical avenues for tailored safety education and platform-based interventions, enabling online marketplaces and policymakers to address the needs of at-risk consumer groups more effectively. Future research may expand the dataset size, integrate additional behavioral factors, and incorporate real-time user interaction data to further enhance the robustness and generalizability of these models.

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