Predicting Consumer Electronics E-Commerce: Technology Acceptance Model and Logistics Service Quality

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Abstract

In online shopping for consumer electronics, information and physical flows are crucial determinants of consumer purchase intentions. This study examines these factors by integrating the Technology Acceptance Model with logistics service quality, analyzing the relationship between retailers and consumers in e-commerce. The focus is on how information and physical flows, as critical supply chain elements, affect consumers' decisions to purchase online. A structural model and machine learning algorithm with SHapley Additive exPlanations are employed to analyze the data, providing a comprehensive analysis of the Technology Acceptance Model in conjunction with logistics service quality. The findings reveal that attitude, perceived usefulness, and informativeness are the most influential factors affecting consumers' purchase intention. This study contributes to the understanding of consumer behavior in the context of e-commerce platforms for consumer electronic products by integrating the Technology Acceptance Model and logistics service quality theoretical perspectives and analyzing the data using innovative techniques, specifically, Shapley Additive Explanations. This research offers valuable insights into the significant role of various features in shaping consumers' purchase intention in the context of online e-commerce platforms for consumer electrical products.

Keywords

Consumer Behavior, Logistics Service Quality, Machine Learning, SHAP (SHapley Additive ExPlanation), Technology Acceptance Model.

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I. Introduction

Due to the growth of the global economy and the prevalence of Electronic Commerce (EC), effective inter-organizational planning and implementation of value chain processes have become indispensable for the success of online retailers. Information and physical flows are crucial for the relationship between retailers and consumers in e-commerce, as they are integral components of the supply chain [1]. In consumer perspective, consumers have incentives to purchase consumer electronics products online rather than offline due to the dynamic nature of the products and their complexity. In the supply chain perspective, in response to the rapid growth of e-commerce, retailers in E-commerce platforms are continuously adapting their distribution network infrastructure [2]. Technological innovations, including wireless technologies such as Radio-frequency Identification [3] [4] and the Internet of Everything [5] [6], have significantly impacted the e-commerce landscape, emphasizing the paramount importance of logistics service quality in maintaining a competitive edge in the dynamic world of online retail. In this regard, the success of online retail heavily relies on various factors, and one crucial determinant is logistics service quality. The ability to excel in logistics operations has become paramount for online retailers to maintain a competitive advantage in the competitive business environment [7]. Furthermore, studies indicate that the quality of physical distribution services is a critical indicator of customer purchase satisfaction [8] and intention to shop online [9]. Nonetheless, limited studies have considered logistics service quality within the theoretical framework of the Technology Acceptance Model (TAM), where the former is related to the supply (firm) side and the latter is related to the demand (end consumer) side. It is surprising that retailers in e-commerce, as part of the supply chain, have not extensively considered the quality of logistics services, despite its potential impact

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on individuals' perceptions and behaviors as end consumers [10]. Given the vital role of logistics service quality in the success of online retailers, it is imperative to explore its influence within established theoretical frameworks. The TAM is a widely recognized framework that explains individuals' acceptance and adoption of technology. Integrating logistics service quality as a factor within the TAM model can provide valuable insights into how it affects customer perceptions, attitudes, and behaviors in the context of online retail when purchasing consumer electronics products. Therefore, this study specifically aims to investigate the influence of logistics service quality as an external factor for consumers of consumer electrical products who use online e-commerce platforms for purchases.

With the ongoing process of economic globalization and the advancement of information technology, electronic commerce has increasingly impacted people's lives [11]. Online shopping, as a viable alternative to traditional shopping, offers numerous advantages. At the end-customer level, online shopping provides a wider selection of goods and services, enabling consumers to easily access product information and compare prices across different distributors [12] [13]. Additionally, consumers can make shopping decisions based on online reviews from other customers [14] [15]. Convenience [16] [17], time and cost savings [12] [18], and flexible transaction methods [17] [18] are among the key factors that drive customers to adopt online shopping. At the firm level, the Internet serves as an effective distribution channel, allowing businesses to reduce costs and overcome geographical barriers [12]. Many businesses have capitalized on this global distribution channel to expand their operations, recognizing it as a substantial growth opportunity [17]. Importantly, electronic commerce strengthens coordination between upstream and downstream supply chain members, fostering cooperation and facilitating technology innovation to enhance operational efficiency. This integration is crucial for businesses to gain a competitive advantage and increase profitability [11]. For instance, in the online environment, consumers conveniently obtain product and retailer performance information from e-commerce platforms, which subsequently influences their purchase intentions [15] [19]. In summary, online shopping provides customers with a wide array of choices, easy access to product information and price comparisons, and the ability to make purchase decisions based on online reviews. Simultaneously, businesses benefit from cost reduction, global expansion opportunities, and improved coordination in the supply chain, leading to enhanced competitive advantage and profitability.

Consumer electronic products, such as digital cameras, smartphones, and DVDs, are a significant and dynamic segment of the global economy [20]. These products are known for their complexity and specialized knowledge requirements for operation and maintenance [21]. In addition, these products undergo frequent updates and introductions of new models, making it challenging for regular consumers to keep up with their technical specifications. Consequently, consumers may end up purchasing electronics that do not meet their expectations in terms of quality [20]. To address this issue, consumers often engage in research activities to gather information about consumer electronics products [14].

When it comes to the pre-purchase stage of buying electrical products, online purchasing offers distinct advantages, particularly in the consumer electronics product category [14]. Online platforms, such as e-commerce websites, provide access to credible user-generated reviews that offer valuable insights into the quality, features, and performance of products. The abundance of online information allows consumers to access diverse opinions and perspectives, enhancing the credibility and reliability of the information they receive. Additionally, after purchasing electrical products, the complexity of these devices necessitates access to detailed product information and technical support. E-commerce platform retailers can provide immediate and non-distance chat-based technical support to assist customers in troubleshooting any product-related issues [21]. Given the significant investment often associated with consumer electronics, online reviews serve as a crucial source of information, helping consumers make informed purchase decisions and avoid potential pitfalls [14]. Therefore, online shopping in e-commerce platforms is the preferred choice for many consumers, especially college students who may lack experience, as it provides access to detailed product information, technical support, and objective reviews. This allows consumers to gather the necessary information to make informed decisions when purchasing consumer electronic products.

However, the supply chain perspective is also crucial in understanding consumers' purchase intentions, particularly when it comes to electrical products, which are physical goods delivered from the supply side to the demand side within the supply chain. While purchasing electronic products online offers numerous advantages, there are also challenges, such as the impact of logistics on consumers' purchase intentions [10]. For instance, during the product delivery stage, many electronic products contain delicate components that can be easily damaged if not handled properly, leading to potential disputes related to returns and exchanges. Effective customer service in online retail involves seamless integration between online ordering and offline delivery, with third-party logistics playing a key role [22]. The differentiation in logistics quality can influence shopping decisions and profitability [23] [24]. Thus, the quality of logistics is central in the supply chain, ensuring the delivery of functional electronic products to end customers [25].

In a theoretical context, research in information systems and e-commerce has explored how users come to accept and utilize new technologies through the Technology Acceptance Model from the perspective of end customers. Logistics service quality is a crucial factor that should be taken into account within the supply chain [10]. Particularly given the complexity and frequent updates of consumer electrical products, on one hand, from an information perspective, product information and technical support are more easily to access from online, facilitating informed purchase decisions in one place. On the other hand, the process of purchasing from the retailer does not end at placing the order on e-commerce platform, as transportation in the supply chain plays a vital role in delivering the product to the end customer. From a transportation perspective, it is important to consider the sensitivity and fragility of consumer electrical products, thus highlighting the need for a framework that incorporates the aspect where the last mile of product delivery is from the retailer to the end customer when investigating the purchasing behavior of consumer electrical products on e-commerce platform.

Prior studies used the methods such as Local Interpretable Model-Agnostic Explanations, Partial Dependence Plots, or ELI5 algorithms in the field of explainable artificial intelligence to interpret and explain machine learning models. However, SHAP's approach to local explanations using Shapley values from game theory is preferred by [26] as it is better than prior techniques. According to some studies [27] [28], Shapley Additive method (SHAP) is better than other statistical methods to interpret the output of machine learning models because it satisfies three key properties: local accuracy, missingness, and consistency. These three properties ensure that the feature attribution method accurately reflects the contribution of each feature to the model output, even when some features are missing or when the model's dependence on a certain feature changes. The SHAP framework is also aligned with human intuition and has a sound theoretic basis, making it suitable for regulated scenarios.

By satisfying these three key properties, the Shapley Additive method provides accurate, comprehensive, and reliable explanations for the prediction of consumer purchase behavior in questionnaire analysis. In the context of consumer purchase behavior in e-commerce platform, local accuracy ensures that the Shapley values correctly attribute the impact of each questionnaire feature on a particular consumer's purchase decision. On the other hand, consistency ensures that the Shapley values provide stable and reliable explanations across similar consumers with similar questionnaire responses. Thus, consistency helps in identifying general patterns and trends in purchase behavior, allowing businesses to make informed decisions based on the reliable interpretation of feature importance. The property of Missingness enables the method to provide meaningful explanations even when certain questionnaire features are not available, improving the applicability and robustness of the analysis. It enables businesses to gain insights into the relative importance of different questionnaire features and understand how they influence consumer decisions. Thus, this knowledge can guide marketing strategies, product design, and customer segmentation, ultimately leading to more effective and targeted approaches to meet consumer preferences and drive sales.

To address the aforementioned issues, this study incorporates the technology acceptance model with logistics service quality to analyze the purchase behavior in consumer electrical products. By building the technology acceptance model, the research examines beliefs, attitude, and purchase intention of end customers to investigate how they accept and use a technology on e-commerce platform. Additionally, logistics service quality was used to capture transportation issue that may affect the end customer accept and use of e-commerce platform for purchasing consumer electrical products. The research aimed to enhance the understanding of consumer behavior in online shopping, offering insights and managerial recommendations to improve logistics operations and customer relationship management in online retailing.

To the best of our knowledge, this is the first study that investigates the purchasing behavior of consumer electric products by incorporating the TAM with logistics service quality. This study contributes to the existing literature in the following aspects. First, the study highlights the inherent complexity and frequent updates of consumer electrical products. By considering the convenience and availability of detailed consumer electrical product information and technical support online, the study emphasizes how individuals' acceptance of technology (online platforms) influences their inclination to purchase consumer electrical products online. Second, the study emphasizes the significance of logistics service quality within the supply chain when investigating consumer purchase behavior on e-commerce platforms. By considering the last mile of product delivery from the retailer to the end customer, the study underscores the importance of transportation and the sensitivity/fragility of consumer electrical products in the purchasing process. This study applies two methods, one for parametric methods and another for non-parametric method. The former analysis confirms the structural model, where the proposed theoretical framework is taken into account, and provides a summary of the overall relationship between the variables. On the other hand, the later one as a complement and robust provides a detailed explanation of how each variable contributes to the prediction. Shapley Additive Explanation method is to interpret the output of the machine learning models and assess the contribution of each feature to the value produced by the model. Third, the research offers valuable insights for both academia and practitioners by providing managerial recommendations. These recommendations enable online retailers to maintain a competitive advantage, promote successful online consumer behavior, and foster profitability in the e-commerce sector.

The following sections are organized in the following manner: in Section II, the related literature is reviewed. Introduction to the method is covered in Section III. The results are included in Section IV. A discussion and conclusion are included in Section V.

II. Literature

This paper aims to investigate the factors that influence consumers' intention to purchase electronic products online. In order to expand upon the TAM, we have introduced logistics service quality as an external variable and incorporated it into the questionnaire design. Through the utilization of a machine learning algorithm, we analyzed the data and applied the SHAP method to interpret the impact of each variable on consumers' ultimate purchase intention. Previous studies have made significant contributions in this field, and in this section, we review the relevant literature encompassing TAM, logistics service quality, and machine learning.

A. TAM Studies

Among the various theories used to predict consumer purchase intention, the TAM has emerged as one of the most widely and successfully employed frameworks in the realm of online consumption. This model has been used in diverse contexts, including clothing [29] [30] [31], luxury products [32], and virtual goods [33] [34] [35]. A study [32] affirms the applicability of TAM in the luxury domain and enriches TAM theory by applying it within the context of online consumer behavior, particularly in the luxury domain. Another research [35] contributes to theory by integrating prospect theory with the TAM to elucidate how perceptions of gains and losses influence the behavioral tendencies of older adults, as well as the role of perceived risk as a barrier to technology adoption. Zhang et al. [31] apply the TAM framework to examine the role of Virtual Try-On (VTO) technology in the online purchase decision-making process of consumers. They explore the relationships between consumers' perceived usefulness, perceived ease of use, perceived enjoyment, and perceived privacy risk with their attitude towards VTO technology, which subsequently influences on their online purchase intention. Although each study has its unique focus and context, their common contribution lies in shedding light on consumer behavior and understanding the factors that influence consumer intentions in various domains. In addition, by incorporating the theoretical foundation of the TAM, researchers can establish a robust and comprehensive framework for studying consumer behavior across various contexts. This framework can effectively elucidate the underlying factors and mechanisms that influence consumer decision-making processes and provide valuable insights for enhancing technology adoption and purchase intentions strategies. The original TAM incorporates key criteria, namely perceived ease of use and perceived usefulness, to gauge the adoption of new technologies. Researchers have expanded the scope of the TAM over time to encompass diverse contexts and concepts, necessitating the inclusion of external components. Table I shows the prior studies where the theory is based on TAM.

On the other hand, some studies have combined the TAM with other issues to predict consumer intentions, such as the Theory of Planned Behavior model [34] [36] [37], task-technology fit theory [38], information adoption model [39], and prospect theory [39]. For example, in their study, Vafaei-Zadeh et al. [37] expanded the combined Theory of Planned Behavior and Technology Acceptance Model by introducing three additional variables to enhance the understanding of purchase intention for electric cars among Generation Y consumers. These variables include price value, perceived risk, and environmental self-image. The results of the study highlight the significant influence of perceived usefulness and perceived ease of use on attitude formation. Furthermore, attitude, subjective norms, perceived behavioral control, price value, and environmental self-image all exhibit positive effects on purchase intention

In summary, e-commerce platforms have become a popular choice for online shopping due to their provision of detailed product

TABLE I. The Summary of TAM-based Studies

Author	Construct	Analysis Method	Theory model	Empirical results	Tools	respondents	context
Liang et al. [66]	Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Performance Risk, Technology Attitudes (TechAtt), Attitude Toward AI (Att), Fashion Involvement (FI), Purchase Intention (PI)	Exploratory Factor Analysis (EFA) Confirmatory Factor Analysis (CFA) Structural Equation Modeling (SEM)	Technology Acceptance Model (TAM)	PU→Att; PEOU→Att; Performance Risk→Att; TechAtt→PI	SPSS 25; Amos 25	313 subjects from the top 10 metropolitan areas in the United States	AI device
Xu et al.[33]	PU, PEOU, Attitude (ATT), Perceived Risk (PR), Group Conformity (GC)	Demographics and Descriptive Statistics; SEM	Extended TAM	PEOU→PU; PEOU→ATT; ATT→PI; PU→PI; PR→PU→PI; GC→PEOU→ATT→PI	IBM SPSS 22.0 and AMOS 22.0	405 young Chinese participants	online paid knowledge
Nguyen et al.[36]	PU, PEOU, ATT, Subjective Norm(SN), PR, Perceived Risk of COVID-19(PRC); Online Shopping Intention(OSI); Online Shopping Behavior(OSB)	Scale reliability test using Cronbach's Alpha, Discriminant and Convergence test using EFA, Pearson's correlation test, Hierarchical regression	Combined Theory of Acceptance Model (TAM) and Theory of Planned Behaviors Model (TPB)	PR→OSB; OSI→OSB	SPSS	638 Vietnamese Internet shoppers	-
Lee and Wong[34]	Personal innovativeness; Subjective Norm(SN); Environmental Consciousness(EC); Price Consciousness(PC);PI; PU; PEOU; Perceived Safety Risk(PSR); Perceived Privacy Security(PPS); Perceived Value(PV); Word-of-Mouth(WoM);	SEM	TAM and TPB	PC→WoM; PU→WoM; PEOU→WoM; PSR→WoM; WoM→PI	SPSS 22.0	277 respondents from social media platforms	on-demand ride-hailing
Wang et al. [38]	Interface Visual Complexity(IVC), Visual Search Efficiency(VSE), Mobile Search(MS), Mobile Payment(MP), Security Precautions(SP), User Experience(UE), Implementation Intentions of Online Shopping(PI)	SEM; Fuzzy-set Qualitative Comparative Analysis (fsQCA)	Task-Technology Fit Theory (TTF) and Technology Acceptance Model (TAM)	VSE→PI; UE→PI; VSE→UE; IVC→VSE; MS/MP/SP→UE	AMOS	College students	-
Rahaman et al.[39]	eWOM Information Quality (IQ); eWOM Information Credibility (IC); eWOM Ease of Use(EOU); eWOM Usefulness (USE); eWOM Information Adoption (INAD); Purchase Intention (PI)	PLS-SEM	Information Adoption Model (IAM) and TAM	USE→PI; EOU→PI; IQ→PI; IC→PI	SPSS 23 SMARTPLS 3.3	College students from Chattogram City of Bangladesh	-----
Lee et al. [99]	Perceived Number of Users(PNOU); Perceived Number of Friends((PNOF)); Perceived Enjoyment(PE); PU; Perceived Desire for Jackpot(PDFJ); PI; Intention to Use(ITU)	CFA; SEM	TAM	ITU→PI; PDFJ→PI; PNOU/PNOF/PE/PU→ITU; PE/PNOF→PDFJ	AMOS 21.0 and SPSS Statistics 21.0	Users of online communities	probability-based items in mobile social network games
Mazzù et al.[69]	PEOU; PU; ATT; PI; Trust Towards the Label (TTL)	CFA; SEM	Front-of-Pack Acceptance Model (FOPAM)	PU→PI; ATT→TTL→PI; PEOU/PU→ATT→PI; PEOU→PU	-	Primary grocery shoppers on Prolific	processed foods
Wong et al.[35]	Perceived Enjoyment(PE); Perceived Effectiveness of Gamification(PEG); Perceived Risks(PR); Adopyion Intention(AI); ATT; PU; PEOU	EFA; CFA; SEM	TAM and Prospect theory	PE→PEG; PU→ATT→AI; PR→AI	SPSS 25.0	Elderly users in residential areas of Suzhou, China	mobile payment.
Wang and Wang[29]	PU, PEOU, ATT, PI, Perceived Performance Risk (PR), Functionality (FUN), Aesthetic (AES); Compatibility (COM)	CFA; SEM	TAM	COM→PU/PEOU/PR; PU/FUN→ATT/PI; PE→PU; PE/AES→ATT; PR→ATT	SPSS; AMOS	-	parent-child smart clothing
Jain [32]	PU, PEOU, ATT, PI, PE, PR, Price Consciousness (PC), Web Atmospherics (WA)	CFA and Hayes Process macro	TAM	PU/PEOU/PE/PC→PI/ATT; ATT→PI	SPSS; AMOS	Luxury fashion consumers in India.	luxury
Vafaei-Zadeh et al.[37]	PU, PEOU, ATT, PR, PI, Subjective Norms (SN), Perceived Behavioural Control (PBC), Price Value (PV), Environmental Self-Image (ESI), Infrastructure Barrier (IB)	PLS (Partial Least Square)-SEM	Combined Theory of Planned Behavior and Technology Acceptance Model (C-TAM-TPB)	PU/PEOU→ATT; ATT/SN/PBC/PV/PR/ESI→PI	-	Generation Y consumers in Malaysia	electric vehicles
Chidambaram et al.[30]	Virtual Try-On (VTO), PU, PEOU, PE, PR; PI	Hayes's Process macros	TAM	Attitude towards VTO mediated the relationship between PU and PI; PR negatively moderated the relationship between PU and Attitude towards VTO; PE positively moderated the relationship between PU and PR and PI mediated through Attitude towards VTO.	-	Millennial respondents in the Southern part of India	online apparel
Zhang et al. [31]	PU, PEOU, PE, PI, Perceived Socialization (PS) Perceived Product Risk (PROR)	PLS-SEM	TAM	PEOU→PU/PE; PU/PE/PRIR→ATT; ATT→PI	-	Online consumers	garment

TABLE II. The Summary of Logistics Service Quality Studies

Author	Factors of logistics service quality	Research variables	Method	finding	respondents
Choi et al.[44]	Quality of Information(QI); Quality of Delivery(QD); Quality of Order(QO); Price of Delivery(PD); Customer Service(CSer)	Service Quality, contain: QI; QO; CSer; PD; Order Procedure (OP); Accuracy(ACC); Order Accuracy(OA); Logistic Service Quality (LSQ); Customer Satisfaction(CSat); Repurchase Intention(RPI)	Validity test; Reliability test; Correlation analysis	QO→CSat; QI→CSat; QD→CSat; PD→CSat; CSer→CSat; CSat→RPI;	Young Chinese customers with experience purchasing products online
Zheng et al. [25]	Order Quality (OQ), Customization Service Quality (CSQ), Response Quality (RQ), Delivery Quality (DQ), Order Discrepancy Handling Quality (ODHQ)	Customer Satisfaction (ECS), Customer Trust (ECT), Customer Loyalty (ECL); OQ; CSQ; DQ; RQ; ODHQ	Exploratory Factor Analysis (EFA); Confirmatory Factor Analysis (CFA); Structural Equation Modeling (SEM)	OQ/CSQ/DQ/ODHQ→ECS; CSQ/RQ/ODHQ→ECT; ECS/ECT→ECL	An online research firm in China
Jiang et al.[45]	Personnel Contact Quality (PCQ); Delivery Quality (DLQ); Infomation Quality (IMQ); Timeliness Quality (TLQ); Empathy Quality (EPQ)	PCQ; DLQ; IMQ; TLQ; EPQ; Satisfaction (SAT); Perceived Importance (PIM)	Hierarchical regression analysis; Importance-Performance Analysis (IPA); SEM	PCQ/EPQ/TLQ/PIM→SAT	Online consumers of fresh food
Hu et al.[100]	Customized Logistics Services (CLS)	Customized Logistics Services (CLS); Satisfaction Level (SAT); Product Type(PT)	EFA; two-way ANOVA	The results indicate that CLS positively impacts SAT. PT does not have moderate effect on the relationship between CLS and SAT.	Tmall.com in China
Oh et al.[42]	Delivery Service Quality(DSQ); Delivery Information Service(DIS); Return Logistics Service(RLS); Delivery Stability(DS); Eco-Friendliness(EF);	DSQ; DIS; RLS; DS; EF; Customer Satisfaction(CS); Intention to Reuse(IRU)	Statistically analyzed	Logistics service quality positively influences CS and IRU (the most significant factor was DS); DSQ/DS/DIS→IRU; CS→IRU	Korean consumers
Dong [43]	Integrity of Delivered(INT); Accuracy of Delivery Time(ADT); The Correctness of the Delivered Goods(CORD); Service Attitude of Delivery Staff(SATT); Delivery Speed(DSP); Whether the Logistics Information is Updated in Time(INF); The Outer Packaging of the Goods is Reasonable and in Good Condition(PAC)	INT; ADT; CORD; SATT; DSP; INF; PAC	Smart sensor technology	Under JD's selfoperated logistics distribution model, users pay the most attention to the INT, ACC, and SATT of the delivery personnel. Under the third-party logistics distribution model of Taobao, the main influencing factors are INT, ACC, PAC	Online evaluation surveys form JD and Taobao

information, technical support, and objective reviews. These features empower consumers to make well-informed decisions when purchasing products. However, the existing literature on consumer behavior in the context of online shopping for consumer electrical products is limited. Given the complex nature and continuous advancements in consumer electronic products, consumers often need to invest more time and effort in evaluating how well these products meet their specific needs and preferences. This includes not only assessing the features and specifications of the products but also considering the post-sale support and functionality. Offline decision-making for consumer electrical products within a short time frame can be challenging. Therefore, this study aims to investigate consumer behavior specifically in the context of online shopping for consumer electrical products.

B. Logistics Service Quality Studies

Online shopping differs from offline shopping in that they are electronic retail markets where goods are transported between individual customers and businesses through logistics. The perception of logistics service quality directly impacts consumers' online purchase intentions. Consequently, researchers recognize logistics service quality as a significant factor impacting consumers' online shopping intention, leading to the continuous development of study on the relationship between logistics service quality factors and consumer purchase behavior. Table II shows the prior studies where the theory is based on logistics service quality.

Some studies examine logistics service quality as an independent variable, along with other factors, to identify consumers' adoption of online purchase behavior [1] [40]. Gao [1] divided the quality of the blockchain system in cross-border e-commerce into three dimensions: commodity information quality, logistics service quality, and payment security. They studied the influence mechanism of blockchain technology application on consumers' willingness to purchase in cross-border e-commerce. Cang and Wang [40] explored the key variables influencing the online purchase intentions of fresh agricultural goods across different customer segments. The findings from hypothesis testing revealed that product quality, online word of mouth, and logistics service quality exert significant influences on potential consumers. However, the study did not find a significant impact of website information quality on potential consumers.

Other studies focus on establishing the key factors determining the quality of logistics services related to online shopping [25] [41] [42] [43] [44] [45], such as timeliness, empathy, information quality, and delivery stability. Through various empirical analysis methods, Oh et al. [42] determined that logistics service quality plays a constructive role in shaping customer satisfaction and intention to engage in future transactions within the context of overseas direct purchases. Specifically, among the various dimensions of logistics service quality, delivery stability emerged as the most influential factor. In another study [43], an examination of e-commerce data and online assessment surveys was undertaken to investigate and evaluate the significance of factors influencing the quality of logistics services and customer satisfaction levels across various distribution models. The findings indicated distinct patterns for different logistics models. Specifically, under JD's self-operated logistics distribution model, users placed high importance on the integrity of delivered goods, the accuracy of delivery time, and the service attitude of the delivery personnel. On the other hand, for Taobao's third-party logistics distribution model, the primary influencing factors included the integrity of delivered goods, the accuracy of delivery time, the importance of outer packaging, and the significance of product integrity. These findings highlight the varying considerations and priorities of customers under different distribution models in terms of logistics quality.

In sum, while numerous studies have explored the impact of logistics service quality on consumer behavior, research specifically focused on consumer electrical products is limited. Nevertheless, it is crucial to take into account the delicate nature of consumer electrical products during transportation. In operation and supply chain perspective, effective product development hinges on customer experience, as the identification and prioritization of pertinent factors contribute to a comprehensive understanding and successful product outcomes [46]. Furthermore, the significance of customer experience aspects varies across distinct product categories [47], suggesting that comprehending these variations would inform product development strategies that align with operation and supply chain strategy. Thus, it becomes necessary to include the final stage of product delivery, known as the last mile, which spans from the retailer to the ultimate customer, when examining the buying patterns of consumer electrical products on e-commerce platforms. This emphasizes the significant role of the perception of logistics service quality in influencing consumers' intention to make online purchases. Integrating the Technology Acceptance Model with logistics service quality helps predict consumers' online purchase intention for consumer electronic products, highlighting the significance of a seamless customer experience in e-commerce.

C. Machine Learning Studies

Machine learning (ML) constitutes a significant and relatively nascent facet of artificial intelligence, involving the training of computer programs to execute tasks and acquire knowledge from the gained experience. As these programs accumulate additional experience, their practical performance in these tasks is enhanced. Consequently, machines can derive decisions and predictions based on data [48]. Table III displays previous studies that utilize questionnaire surveys to predict outcomes in diverse scenarios.

Several investigations have utilized questionnaire data and applied machine learning techniques to predict consumers' propensity to purchase electric vehicles [49] [50] [51] [52]. Additionally, studies have examined purchase behavior or intention for other products, such as "holiday homes" [53], self-defense tools [54], and organic products [55]. Commonly, these studies assess the performance of diverse machine learning algorithms, including Random Forest (RF), Logistic Regression, Decision Trees, Support Vector Machine (SVM), Gradient Boosted Trees (XGBoost, CatBoost, etc.), and Neural Network (KNN, ANN, etc.), to ascertain the most effective one. The choice of optimal algorithms varies depending on the specific context. For instance, Taghikhah et al. [55] applied four machine learning algorithms (SVM, LR, DT, and RF) to analyze consumers' wine preferences, and the RF algorithm yielded the highest accuracy of 89%. Conversely, in another study [56] concerning the application of machine learning in differentiating dampness-heat patterns in patients with type 2 diabetes mellitus in Chinese medicine, SVM outperformed RF.

In real-world machine learning applications, interpretability of models can at times outweigh accuracy [57]. The SHAP method is employed to interpret predictions made by the most effective machine learning models by quantifying and ranking the significance of each variable to the target variables. Within the medical domain, Ballester et al. [58] utilized the XGBoost model to assess predictors of suicide risk and employed graphical representations of SHAP values to interpret the associations of each variable with the outcome, revealing whether it acts as a protective factor or a risk factor. Similarly, Huang and Huang [59] employed Shapely Additive Explanations to visualize the relationships between continuous covariates and the risk of sleep disorders utilizing the National Health and Nutrition Examination Survey dataset. Fan et al. [60] developed various machine-learning models based on tryptophan hydroxylase-2 methylation and environmental stress to identify patients with major depressive disorder. SHAP values were utilized to demonstrate the differential effects of each feature on the outputs of the BPNN model. In their study, higher SHAP values corresponded to a higher probability of patients having a major depressive disorder.

To summarize, SHAP provides a visual, intuitive, and comprehensive approach to augment the interpretability of ensemble models. It aids in comprehending and interpreting the entire model, as well as visualizing feature attributions at the individual observation level for any machine learning model [57]. This paper represents the initial attempt to incorporate the interpretability of machine learning models in predicting consumers' purchase intentions. Whereas preceding studies have predominantly focused on enhancing the accuracy of purchase intention models, this paper presents the initial endeavor to employ SHAP values and associated visualizations in the quest to enhance the explainability of the TAM with respect to logistics service quality. By exploring the underlying factors that drive consumers' purchasing behavior, this research aims to enhance the understanding and applicability of the TAM with the logistics service quality framework. Through the utilization of SHAP values, researchers can gain valuable insights into the relative importance of different variables, thereby improving the transparency and interpretability of machine learning models in predicting and explaining consumers' purchase behavior.

III. Hypotheses

A. Hypotheses

Logistic Service Quality is defined as "logistics services relating to all the problems in the process of shipping goods"[44]. Logistics plays a crucial role in facilitating the transfer of goods from suppliers to consumers. In the context of e-commerce, where transactions occur remotely without face-to-face interactions between consumers and salespeople, the quality of logistics service assumes a role similar to that of sales staff in traditional retail settings [42]. As a result, the quality of logistics service directly influences consumers' perception of their online shopping experience. It has been confirmed that logistics fulfillment quality has a significant influence on the perceived usefulness of e-procurement services [10]. Fu [61] found that management service, platform technology, and the application effect of an intelligent logistics information platform have significantly positive influences on the user's perceived ease of use. Furthermore, the security of using delivery drones by logistics service providers will significantly influence consumers' perceived ease of use of this new technology [62]. Prior research has established a significant relationship between users' perceived ease of use of IT tools and logistics process quality [63]. Similarly, Jain et al. [64] found a positive correlation between mobile service quality, encompassing both forward and reverse logistics, and consumers' perceived usefulness of mobile shopping. In light of this, we have introduced logistics service quality as an innovative external variable within the TAM framework. Based on this premise, we propose the following hypothesis:

Hypothesis 1: The influence of consumers' perception of logistics service quality on perceived usefulness in the context of online e-commerce for purchasing consumer electronic products is significant.

Hypothesis 2: The influence of consumers' perception of logistics service quality on perceived ease of use in the context of online e-commerce for purchasing consumer electronic products is significant.

Perceived ease of use in TAM is defined as the "degree to which an individual believes that the usage of a particular technology does not

TABLE III. Attributes, Algorithms, and Data Mining Techniques Frequently Used to Predict Questionnaire Surveys in Various Scenarios

Author	Attributes/Variables used	Algorithm	Performance	Data mining technique	Tools	Preprocessing Technique
Li et al. [53]	Enduring Involvement,Destination Familiarity,Place Attachment,Purchase Intention,Air Quality, Air Quality, Age, Gender, Education, Income, Package Tour, Family, Friend, Colleague, Travel Experience	Decision Trees (DT), Support Vector Machine(SVM), AKMC	AKMC=82%; KNN=53%; DT=58%; SVM=53%	Classification, Clustering	MATLAB; R2019b	Correlation analysis
Borres et al.[54]	Understanding Safety, Perceived Risk, Self-Effificacy, Perceived Severity, Perceived Behavioral Control, Subjective Norm, Attitude, Perceived Safety, Purchase Intention, Buying Impulse	DT, Random Forest Classifier (RFC), and Deep Learning Neural Network (DLNN)	DT<60%; RFC=96%; DLNN=97.7%	Classification, Neural Network	SPSS 25, Python	Normalization, Correlation analysis
Jia et al.[50]	Electric Vehicle,Household income,Home own,Household size,Young child,Household vehicle,Urban rural,Population density,Price,Place,Age,Gender,Education,Race,Multi-job,Occupation,Car sharing, Time to work,Year mile	DT, Random Forest (RF), Logistic Regression (LR), Naïve Bayes (NB)	NB=0.878; LR=0.795; RF=0.999; SVM=0.993; DT=0.999	Classification, Regression	Python	Synthetic Minority Over-sampling Technique (SMOTE)
Jia [49]	Household income, Home own, Houschold size, Young child, Household vehicle, Urban rural, Population density, Price, Place, Age, Gender, Education, Race, Multi-job, Occupation, Car sharing, Time to work, Year mile	LR, NB, SVM, DT, RF	NB=0.650; LR=0.661; RF=0.924; SVM=0.888; DT=0.908	Classification, Regression	Python	Factor analysis; Regression analysis; SMOTE
Shu et al. [51]	Range Anxity, Climatic Conditions, Technical Maturity, Radation Injury, Physical Discomfort, Accident, Cost-in-use, Acquisition Cost, Maintenance of Value, EV Charging Facilities, Charging Time, Charging Convenience , Social Needs, Preference and Trust Rank, Environmental Conservation	BERT-Att-BiLSTM BERT-TextCNN	BERT-TextCNN (MaF1=0.92); BERT-Att-BiLSTM(F1=0.90)	NLP, Classification	Python	Labels classification, Semantic identification, Emotion analysis.
Sobiech-Grabka et al. [52]	Period of availability, Available amount of subsidy, Limit of car price, Eligible cars, Weakness	Classification and Regression Trees (CART); KNN; SVM; RF	CART=0.870 KNN=0.830 SVM=0.943 RF=0.9867	Classification, Regression, Neural Network	Python	Descriptive statistics
Christidis and Focas [101]	Age, gender, living area, availability of cars and public transport, frequency of trips, duration, distance, inter-modality, Long-distance trips, Attitude	Gradient Boosting	AUC≈0.80	Classification	Python	Descriptive statistics
Lu et al. [48]	Perceived usefulness, Perceived ease of use, Consumer factors, Cross-border e-commerce platform factors	ML	-	Deep Learning, Neural Networks	SPSS, Python	Descriptive statistics; Regression analysis
Carreón et al.[102]	Advert Viewing Time, Purchase Intention, Demographics	SVM, XGBoost, LR	-	Classification, Gradient Boosted Regression Tree, Regression	SPSS, Python	t-test
Taghikhah et al. [55]	Gender, Age, income, Average household size, Education level, Attitude, Perceived Behavioral Control, Habit, Hedonic goals, Gain goals, Normative goals, Social norms, Emotions, Spontaneous urge	SVM, LR, DT, RF	3 classes:(Acc) SVM=78%, LR=78%, DT=86%, RF=89%	Classification, Regression, Density-based clustering	Python	Standardization descriptive analysis, Correlation analysis
Ballester et al. [58]	General Health, SocloeconomIc Status, SRQ-20 Total Score, Bodily Paln, Physlcal Functloning, currently Studying, Sex, Wtalty, Mental Health, Age	XGBoost	XGBoost (AUC=0.71)	Gradient Boosted Trees; SHAP	R	Statistical analysis
Ghorbany et al.[103]	20 KPI indicators, such as Financing Cost, Value for Money, Construction Period, etc.	Copula Bayesian Network (CBN)	CBN=91%	Neural Network, SHAP	SPSS, Python	Statistical analysis; Correlation analysis
Liu et al. [56]	Slimy yellow tongue fur, Slippery pulse or rapid-slippery pulse, Sticky stool with ungratifying defecation, Red tongue, Bitter taste in mouth, Obesity, Thick tongue fur, Halitosis, Dry mouth and thirst, Sticky and greasy in mouth, Heavy body, Constipation, Deep-colored urine, Heavy sensation of head	ANN, KNN, NB, SVM, XGBoost, RF	AUC: XGBoost=0.951; SVM=0.945; ANN=0.947; KNN=0.922; NB=0.922; RF= 0.941	Neural Network; Gradient Boosting; Classification; SHAP	python	-
Fan et al. [60]	gender, CTQ and NLES scores, 25 TPH2 CpG sites (TPH2–11–86, TPH2–11–121, TPH2–11–154, etc.)	BPNN, RF, RBF-SVM, POLY SVM	AUC: RBF-SVM=0.864; POLY SVM=0.832 BPNN=0.988 RF=0.906	Neural Network; Classification; SHAP	Python, SAS, R	Normalization

TABLE III. Attributes, Algorithms, and Data Mining Techniques Frequently Used to Predict Questionnaire Surveys in Various Scenarios (Cont.)

Author	Attributes/Variables used	Algorithm	Performance	Data mining technique	Tools	Preprocessing Technique
Yao et al. [90]	Gender, Age, Marriage status, Education, Working years of psychotherapy, Practice qualification, Licensed psychiatrist, Have professional supervisor, Have professional personal experience, Professional background, Assessment of possible side effects in psychotherapy, Possible causes of side effects in psychotherapy.	RF, XGBoost, CatBoost, LR, AdaBoost, SVM	AUC: RF=0.717, XGBoost=0.689, CatBoost=0.694, LR=0.675, AdaBoost=0.653, SVM=0.629	Classification; Gradient Boosting; SHAP	Python	SMOTE
Huang and Huang [59]	Variables from The National Health and Nutrition Examination Survey	XGBoost, RF, AdaBoost, ANN	XGBoost=0.87, RF=0.82, ANN=0.83, AdaBoost=0.84	Neural Network; Classification; Gradient Boosting; SHAP	Python	Statistical analysis
Ramkumar et al.[104]	Age, Weight, Height, Body mass index, Baseline data (SF-36 pain, KOS-ADL, IKDC Subjective etc.)	GNB; XGBoost; RF; LR; isotonically calibrated XGBoost; sigmoid calibrated XGBoost; and an ensemble soft-voting classifier composed of LR, RF, and XGBoost.	Model for MCID (AUC) GNB=0.72, LR=0.88, isotonic=0.74, RF=0.86, sigmoid=0.94, Ensemble=0.81,	SHAP; Gradient Boosting; Neural Network	Python; R	All ordinal variables were converted to continuous variables.
Wang and Xu [105]	Basic data features, user features, product features, and user product features, totaling 30 features	Fuzzy Support Vector Machine (FSVM); AdaBoost-FSVM; AdaBoost-SVM; SVM; LR; RF; XGBoost	ACC: AdaBoost-FSVM =0.849; AdaBoost-SVM = 0.8112; FSVM=0.7912; SVM=0.7704; LR=0.7616; RF=0.7899; XGBoost=0.8080	Classification; Regression	Python	Select valuable features

require extra effort", On the other hand, perceived usefulness is "the degree to which a person believes that using a particular system would enhance his or her job performance" [65].

Considering the complexity inherent in consumer electronic products, online shopping offers consumers the advantage of intuitive parameter comparisons and access to word-of-mouth recommendations from other users. Furthermore, online shopping enables consumers to make purchases anytime and anywhere, eliminating the need for a substantial continuous time allocation. This enhanced convenience facilitates efficient selection of the most suitable electronics. As a result, consumers are more likely to develop a favorable attitude towards purchasing consumer electronic products online. Notably, a consistent pattern of findings has emerged from prior research employing the TAM framework across diverse domains, highlighting the profound influence of individuals' perceptions on consumer attitudes. This robust association has been observed in various contexts, including electric vehicles [37] [66], mobile food ordering apps [67], ride-hailing services [34], and mobile payment platforms [35]. Building upon the aforementioned discussion, we propose the following hypothesis:

Hypothesis 3: Perceived usefulness positively influences consumers' attitude towards purchasing electronics online.

Hypothesis 4: Perceived ease of use positively influences consumers' attitude towards purchasing electronics online.

Attitude refers to "an individual's positive or negative feeling regarding performing the target behavior". According to the theory of reasoned action, an individual's behavioral intention is contingent upon their attitude towards the behavior [68]. Previous research has consistently demonstrated the impact of consumers' attitudes on purchase intentions across various online domains, including online grocery shopping [69], online luxury products [32], and online garment retailing [31]. Hence, we propose the following hypothesis:

Hypothesis 5: Consumers' attitude towards online purchasing positively influences their intention to use online channels for purchasing consumer electronic products.

B. Research Model

Drawing on the theoretical underpinnings of the TAM, this research endeavors to construct a comprehensive framework (see Fig. 1) that incorporates the dimension of logistics service quality. By delineating a set of constructs and their associated hypotheses, the study seeks to investigate the determinants that influence the purchase intention of online consumers in the context of consumer electronic products.

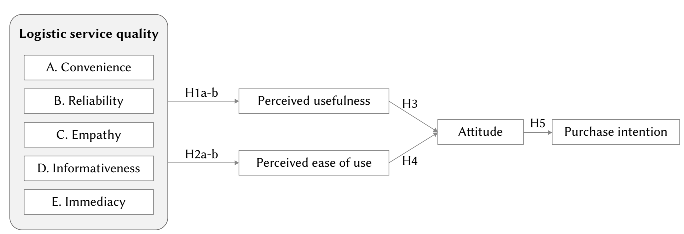


Fig. 1. Conceptual framework.

IV. Method

Fig. 2 presents a comprehensive flowchart that illustrates our methodological process. This flowchart provides a detailed step-by-step description of the methodological process, including survey design, data collection, data processing, model selection, and interpretation.

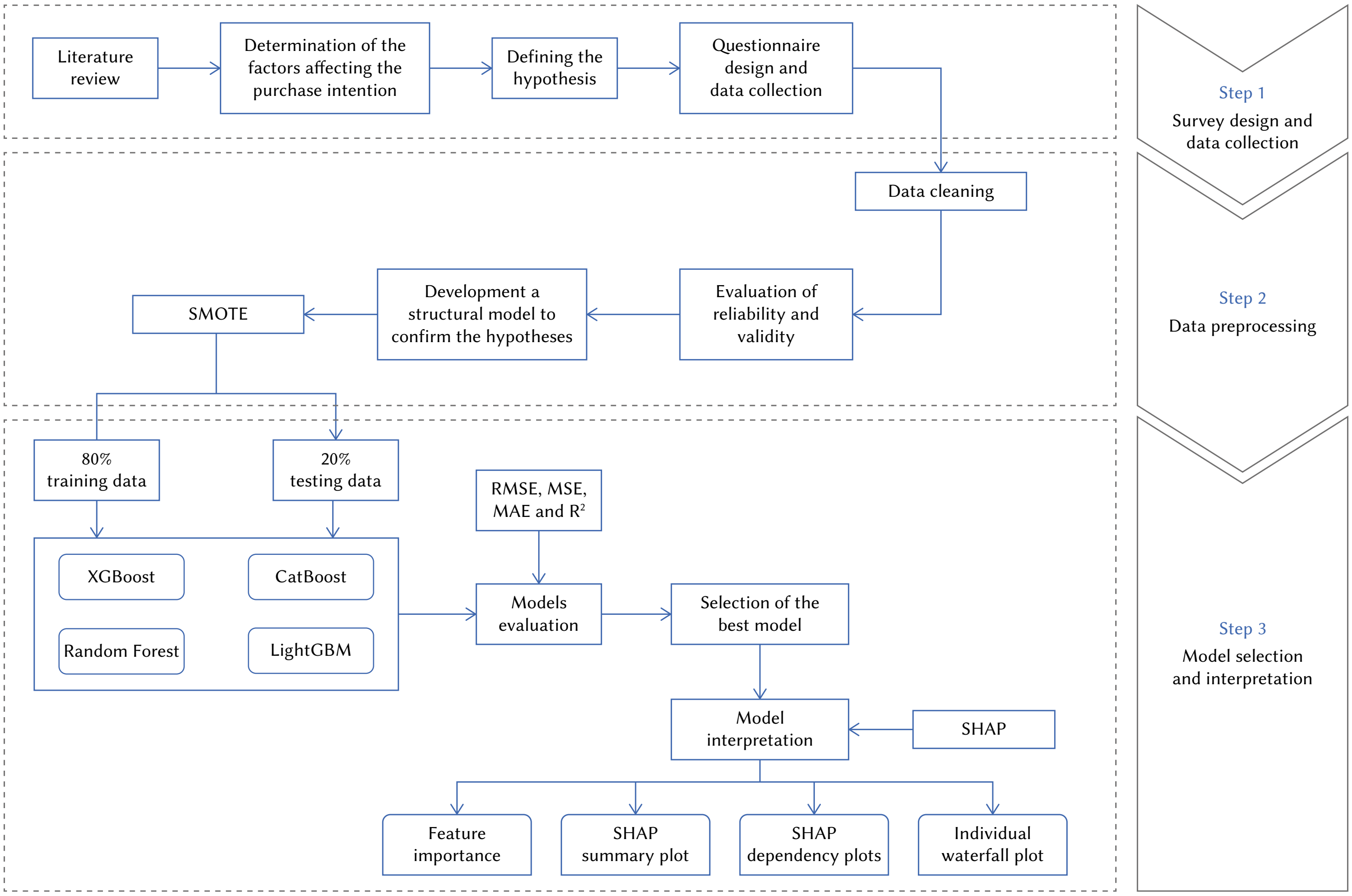


Fig. 2. Methodological process.

A. Techniques

1. Structural Model

SPSS and AMOS, a widely acclaimed and extensively employed statistical software package, provides a diverse array of statistical analysis tools that are instrumental in investigating the TAM with logistics service quality. In the specific context of this study, the utilization of SPSS empowers us to undertake meticulous statistical analyses. AMOS enables the examination of the structural model, which encompasses the relationships between variables and hypothesis testing within the framework of the TAM with a focus on logistics service quality. The employment of SPSS and AMOS ensures the rigor and dependability of the analyses conducted in this study, consequently enhancing the credibility of the research outcomes.

2. Machine Learning Algorithms & Interpreter

For our data analysis, we have employed Random Forest [70], which is widely recognized and has shown excellent predictive performance in recent years. In addition to Random Forest, we have also utilized three other algorithms known for their robustness and effectiveness in prediction: LightGBM, CatBoost [71], and XGBoost [72].

These algorithms possess distinct principles and characteristics. RF is an ensemble learning model that combines multiple Decision Trees (DTs) to achieve predictions with higher accuracy and robustness compared to an individual DT [73].

The computation can be performed using the equation (1) [70]:

$$\mathrm{GiniInde} \;=\; \sum \sum_{j\neq i} \left(\frac{f(Y_i\ ,T)}{|T|}\right)\left(\frac{f(T_j,T)}{|T|}\right) \tag{1}$$

where, *T* presents the training dataset.

$\frac{f(Y_i\ ,T)}{|T|}$ presents the probability of belonging to category Y_i.

Prokhorenkova et al. [71] introduced CatBoost, a novel gradient boosting technique that effectively handles category features while minimizing information loss. Distinguished from other gradient boosting methods, CatBoost initially applies ordered boosting, which is a modified and efficient gradient boosting technique. This approach proves advantageous for small datasets and effectively handles category features. The underlying base predictor in CatBoost consists of binary decision trees. The estimated output can be calculated as shown in equation (2) [71] [74]:

$$Z \;=\; F(x_i) \;=\; \sum_{j=1}^{j} b_j\, 1_{\{x\in R_j\}} \tag{2}$$

where $F(x_i)$ is the function of the decision tree of the independent variables x_i, and b_j is the disjoint region that corresponds to the tree's leaves.

The XGBoost algorithm [72] has gained significant popularity across various domains in recent years. Built upon the concept of "boosting," XGBoost combines the predictions of multiple weak learners using additive training techniques to construct a robust learner. To mitigate overfitting and enhance performance, XGBoost incorporates a regularized method formulation [75]. The integrated framework employs random sampling to reduce variance and improve the predictive capabilities of the final model. The estimated output can be calculated as indicated in equation (3) [72]:

$$Z \;=\; H(x_i) \;=\; \sum_{t=1}^{T} f_t\,(x_i) \tag{3}$$

where x_i represents the independent variables, and $f_t(x_i)$ is each tree output function.

TABLE IV. Questionnaire for Technology Acceptance Model and Logistics Service Quality

When I choose e-commerce way to purchase consumer electronic products online,

Convenience	Qa1: The convenience of payment enhances my online shopping experience.
	Qa2: Setting the pick-up time from logistics is convenient.
	Qa3: Returning goods is convenient.
Reliability	Qa4: The logistics service provider consistently delivers services as promised.
	Qa5: The order delivery process is smooth and hassle-free.
	Qa6: The logistics service providers accurately process my orders according to my requirements.
Empathy	Qa7: The logistics services provided are flexible and customizable.
	Qa8: The transportation and delivery time is appropriate.
	Qa9: The logistics service provider understands my demands well.
Informativeness	Qa10: I can easily access timely and accurate logistics distribution information.
	Qa11: It is easy for me to check the logistics distribution information.
	Qa12: I receive complete and sufficient feedback regarding logistics distribution information.
Immediacy	Qa13: The time between placing an order and receiving the delivery is short.
	Qa14: Deliveries arrive on the promised date.
	Qa15: The back-order time for requisitions is minimal.
Perceived usefulness	Qd1: Buying consumer electronic products online improves my shopping efficiency.
	Qd2: Shopping for consumer electronic products online makes the shopping process easier for me.
	Qd3: Buying consumer electronic products online enhances my shopping ability.
Perceived ease of use	Qb1: It is convenient to purchase consumer electronic products using an e-commerce platform.
	Qb2: It is easy to understand how to buy consumer electronic products using an e-commerce platform.
	Qb3: Learning to purchase consumer electronic products online is effortless for me.
	Qb4: Buying consumer electronic products through an e-commerce platform does not require much mental effort.
Attitude	Qc1: I have a positive attitude on purchasing consumer electronic products online.
	Qc2: Using an e-commerce platform to buy consumer electronic products is a good idea.
	Qc3: It makes sense to purchase consumer electronic products online.
Purchase intention	Qf1: I am likely to buy consumer electronic products online.
	Qf2: I am inclined to consider purchasing consumer electronic products online.
	Qf3: It is certain that I will explore buying consumer electronic products online.

LightGBM, a gradient-boosting decision tree algorithm, has been proposed by Microsoft Research. Acknowledged for its rapidity and exceptional performance, LightGBM finds applications in a variety of machine learning tasks, including ranking, regression, and classification. The primary objective of this algorithm is to enhance computational efficiency in resolving challenges related to predictive analysis on large-scale datasets [76]. The mathematical expression representing LightGBM is provided in equation (4) [77]:

$$F_M(x) = \sum_{m=1}^{T} \gamma_m h_m(x) \tag{4}$$

where M represents the maximum number of iterations and h_m (x) denotes the base decision tree.

The SHAP algorithm [26] offers a method to determine the impact of features in tree-based models, addressing the absence of a direct prediction equation in Decision Trees (DTs) and their derivatives. SHAP values quantify each feature's average marginal contribution, enhancing the understanding of model predictions. This interpretation can be achieved using the shap.explainers.tree function within the SHAP package, which analyzes the trained model and test data predictions [78]. Unlike traditional feature importance analysis, SHAP provides detailed insights into how features affect individual predictions, highlighting their positive and negative impacts on the outcome. This approach, based on the Shapley value from game theory, allocates "credit" to features, allowing for a nuanced understanding of model behavior [26] [79]. SHAP's methodology, applying game-theoretic principles to model interpretation, offers a comprehensive framework for analyzing feature contributions across various machine learning techniques [80]. Notably, in this particular study, algorithms such as CatBoost were employed for conducting the SHAP analysis. Based on several axioms to help fairly allocate the contribution of each feature, shapely values are represented by equation (5) [26] [79]:

$$\emptyset_i = \frac{1}{|N|!} \sum_{S \in N(i)} \frac{|S|!(|N|-|S|-1)!}{N} [f(S \cup \{i\}) - f(S)] \tag{5}$$

where f(S) corresponds to the output of the CatBoost model, S to the set of features, and N represents the whole set of entire features. The ultimate contributions or Shapley value of feature i($\emptyset_i$) is calculated as the average of its contributions over all permutations of a feature set.

Consequently, the inclusion of features into the set is performed individually, and the resulting change in the model's output serves as an indicator of their significance. This approach leverages the utilization of feature orderings, which play a pivotal role in influencing the observed variations in the model's output, particularly in cases where correlated features are present.

B. Research Methodology

1. Data Collection

The questionnaire was developed based on the conceptual framework and hypotheses delineated above, aiming to investigate the factors influencing consumers' online purchase intention of consumer electronic products. The items measuring Convenience and Reliability were adapted from the work by Jiang et al. [81]. Empathy was adapted from other works [82] [83]. Informativeness was adapted from the study by Jiang et al. [45]. Immediacy was adapted from the study by Huang et al. [84]. Perceived usefulness was adapted from the work by Jain [32]. Perceived ease of use and Purchase intention were adapted from the study by Lee and Wong [34]. Attitude was adapted from the work by Mazzù et al. [69]. Table IV displays the questionnaires used in this study, which were translated from Chinese to English. In total, 32

TABLE V. The Results of Reliability & Validity

Constructs	KMO	Cronbach's Alpha	CR	AVE
Convenience	0.68	0.73	0.85	0.65
Reliability	0.65	0.66	0.82	0.60
Empathy	0.69	0.74	0.85	0.66
Informativeness	0.63	0.63	0.80	0.58
Immediacy	0.67	0.69	0.83	0.61
Perceived usefulness	0.78	0.78	0.86	0.60
Perceived ease of use	0.78	0.81	0.87	0.63
Attitude	0.68	0.74	0.85	0.66
Purchase intention	0.70	0.78	0.87	0.69

items were included in the questionnaire, addressing these influential factors. The response options for all items utilized a five-point Likert scale, ranging from 1 = "strongly disagree" to 5 = "strongly agree." Sampling error refers to the statistical variation that arises when a sample does not perfectly represent the entire population. To collect the data for this study, an online survey was conducted from March 26, 2022, to September 7, 2022, employing the SO JUMP platform, a renowned Chinese Internet-based survey platform akin to Amazon Mechanical Turk. This survey leveraged prominent Chinese social media conduits, including WeChat, QQ, and Weibo, to disseminate the instrument. The respondent pool consisted of a random sampling of users across these platforms, ensuring a broad demographic representation. A total of 1323 questionnaires were collected, and after removing any invalid responses, 1069 questionnaires were deemed suitable for further analysis. The sample profile showed that 45.5% of the respondents were female and 55.5% were male. Among them, 2.5% were freshmen, 34.9% were sophomores, 23.8% were juniors, 16% were seniors, 22.5% were graduate students, and 0.3% were doctoral students. This approach was designed to minimize sampling error, ensuring the representativeness and validity of our findings. To enhance the accuracy of the research findings, a reliability analysis and a validity analysis were performed on the questionnaire. These analyses aimed to ensure the robustness and accuracy of the collected data.

2. Reliability & Validity

An initial evaluation of reliability was performed using Cronbach's alpha and composite reliability measures, adhering to the suggested thresholds of 0.60 [85] [86] and 0.7 [87], respectively. The reliability results for the constructs are presented in Table V, indicating that all constructs surpassed the minimum values of 0.6 and 0.7 for Cronbach's alpha and composite reliability, respectively. These outcomes provide robust evidence supporting the instrument's reliability.

In terms of construct validity, the assessment focused on evaluating convergent validity [87]. Convergent validity is deemed to be established when the Average Variance Extracted (AVE) of a construct surpasses the threshold of 0.50 [87]. The findings of the convergent validity analysis, presented in Table V, reveal that the AVE values for all constructs exceed 0.50, substantiating the model's constructs in terms of convergent validity.

C. Preprocessing

Following the reliability test and data cleaning process, a total of 1069 remaining data points were selected for implementation in the machine learning algorithm. To represent the feature values of each factor, we calculated the mean of the question scores associated with that particular factor. Subsequent analysis revealed that a majority of the samples exhibited high scores across all feature values. For instance, considering the target variable of purchase intention, it was observed that only approximately 5% of the samples possessed scores below 3. This significant data imbalance can potentially lead to issues such as overfitting or substantial prediction errors when employing machine learning algorithms. To address this situation, we opted to focus solely on the feature values of the target variable. Each value of the target variable was treated as a distinct category, and the Synthetic Minority Over-sampling Technique (SMOTE) [88] was applied to generate new samples based on the original data. In their study, the generated samples can be denoted as follows:

$$S_{new} = S_i + \omega(S' - S_i) \tag{6}$$

where, S_i presents the samples belonging to minority category. S' is the selected sample close to S_i. ω defines the weight.

Oversampling techniques increase the representation of minority category samples by duplicating them, risking overfitting in models. In contrast, undersampling reduces the sample count by removing random samples, potentially wasting valuable data [50]. SMOTE stands out by generating new, unique samples, thus better supporting prediction models and avoiding the drawbacks of simple duplication [50]. Beyond its common use in addressing class imbalance, SMOTE has been applied in survey research, enhancing data quality and analysis [89] [90]. In this study, using SMOTE resulted in a balanced dataset of 3344 samples, supporting in the effective evaluation and comparison of predictive models.

V. Results

A. Structural Model

The aim of this study is to examine the impact of logistics service quality, as an external factor, on consumers of consumer electrical products who utilize online e-commerce platforms for their purchases. First, to validate the theoretical model established, this study employed a structural model to confirm the conceptual framework. Based on the conceptual framework of this study in Fig. 1, the path coefficients and their corresponding levels of significance in the structural model are presented as follows.

Convenience (β = 0.227, p = 0.000), reliability (β = 0.143, p = 0.000), informativeness (β = 0.13, p = 0.000), and immediacy (β = 0.388, p = 0.000) were found to have positive influences on perceived usefulness. However, empathy (β = -0.013, p = 0.652) did not have a significant effect on perceived usefulness. Therefore, H1a, H1b, H1d, and H1e were supported, while H1c was not supported. Additionally, convenience (β = 0.041, p = 0.309), reliability (β = -0.064, p = 0.144), and informativeness (β = -0.017, p = 0.713) did not have a significant effect on perceived ease of use. However, empathy (β = 0.115, p = 0.006) had a positive impact, and immediacy (β = -0.093, p = 0.035) had a negative impact on perceived ease of use. Thus, H2a, H2b, and H2d were not supported, but H2c and H2e were supported. Furthermore, perceived usefulness (β = 0.676, p = 0.000) positively influenced attitude, and attitude (β = 0.073, p = 0.000) positively influenced purchase intention. Therefore, H3 and H5 were supported. However, perceived ease of use (β = -0.02, p = 0.448) did not have an effect on attitude. Thus, H4 was not supported.

In sum, convenience, reliability, informativeness, and immediacy positively impact perceived usefulness, but empathy does not significantly influence it. Only empathy has a positive influence, and immediacy has a negative impact on perceived ease of use. Perceived usefulness positively affects attitude, which in turn positively impacts purchase intention. However, perceived ease of use does not significantly influence attitude.

B. EML Models Training and Testing

This research aims to compare the predictive performance of various EML models, such as XGBoost, CatBoost, LightGBM, and RF, in forecasting consumer purchase behavior on e-commerce platforms. Utilizing questionnaire data enhanced with SMOTE, the study involves supervised EML training and testing, dividing the dataset into an 80% training set and a 20% testing set, with analysis conducted using Python. Parameter optimization for each EML model is crucial for predictive accuracy, involving a grid search via scikit-learn to fine-tune parameters like 'learning_rate', 'n_estimators', and 'max_depth' to enhance model performance and prevent overfitting. These parameters are detailed in Table VI.

TABLE VI. EML Methods Tuning Parameters

Regression Method	Leaning_rate	n_estimators	max_depth
XGBoost	0.2	100	12
CatBoost	0.1	300	10
LightGBM	0.2	500	05
RF	-	800	10

C. Comparison of EML Model Performance

In this study, EML algorithms (RF, CatBoost, LightGBM, and XGBoost) were evaluated using questionnaire data, with their performance compared across metrics like RMSE, MSE, MAE, and R2, detailed in Table VII. The results showed that the training set consistently yielded higher R2 and lower error metrics than the test set for all models, indicating no overfitting. Table VII shows the comparison of the models' predictive accuracy. Notably, CatBoost emerged as the most effective model, achieving the highest R2 value of 0.889 and the lowest values in RMSE (0.386), MSE (0.149), and MAE (0.235), emphasizing its superior predictive performance in this context.

D. Feature Analysis

The interpretability of most ML algorithms has been subject to criticism due to the challenge of comprehending the importance of features and the contribution of individual predictor variables to the final model outcome. However, the development of an accurate online purchase intention prediction model is crucial, as more precise models can effectively capture the relationships between explanatory and response variables. Moreover, it is essential to interpret the model results and translate them into actionable insights. To address these concerns, this study employed a feature importance analysis based on CatBoost to establish the relative ranking of input variables. Furthermore, partial dependence plots using SHAP analysis were employed to gain additional insights into model interpretability, along with an examination of individual sample observations through a waterfall plot.

1. Feature Importance Analysis

The findings depicted in Fig. 3 provide valuable insights into the significant role of various features in shaping consumers' purchase intention within the realm of online e-commerce platforms for consumer electrical products. Notably, attitude emerges as the most influential factor, highlighting the crucial role of consumers' overall attitude towards platform usage in their purchase decisions.

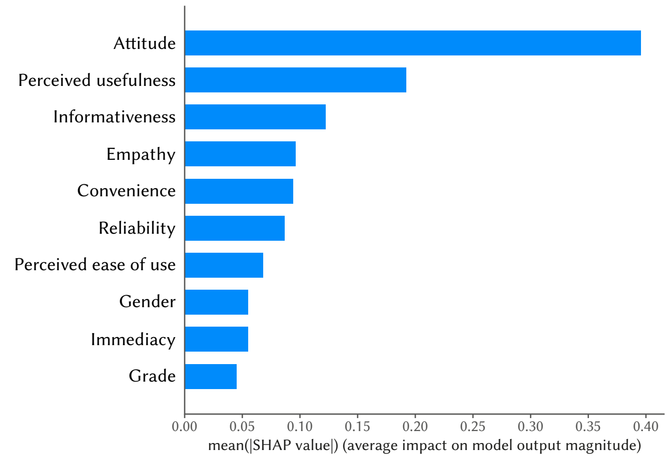


Fig. 3. Features importance using SHAP for CatBoost.

Following attitude, perceived usefulness, and informativeness demonstrate substantial impact on consumers' purchase intention. This underscores the significance consumers place on the practical benefits and logistics-related information provided by the platform during product delivery. The platform's ability to effectively convey useful information and ensure efficient product delivery significantly influences consumers' decision-making process.

Among the moderately important features, empathy exerts its influence on consumers' purchase intention. This finding suggests that consumers' perception of a logistic company's understanding and consideration of their needs plays a role in influencing their decision to engage in online purchases. Additionally, convenience, reliability, and ease of use are identified as contributing factors, albeit to a lesser extent.

Conversely, gender, immediacy, and grade exhibit low importance, indicating their minimal impact on consumers' purchase intention in the context of online purchases for consumer electrical products. This finding implies that consumers' gender, the immediacy of their purchase decision, and their academic grade have negligible influence on their decision-making process in this specific domain.

2. SHAP Summary Analysis

The SHAP summary plot for the CatBoost model, as seen in Fig. 4, visually communicates the significance and impact of various features on purchase intention. The y-axis arranges features based on their mean absolute SHAP values, illustrating their importance, while the x-axis displays the SHAP values themselves. Each feature is represented as a row in the plot, where the color signifies the feature's effect on purchase intention. A secondary color scale on the y-axis

TABLE VII. Accuracy Metrics of EML Methods for Train and Test Set

Models	Train set result				Test set result			
	R^2	MAE	RMSE	MSE	R^2	MAE	RMSE	MSE
RF	0.935	0.201	0.293	0.086	0.835	0.313	0.220	0.469
CatBoost	0.995	0.043	0.078	0.006	0.889	0.235	0.386	0.149
LightGBM	0.977	0.116	0.175	0.031	0.863	0.280	0.428	0.183
XGBoost	0.998	0.022	0.051	0.003	0.866	0.241	0.423	0.179

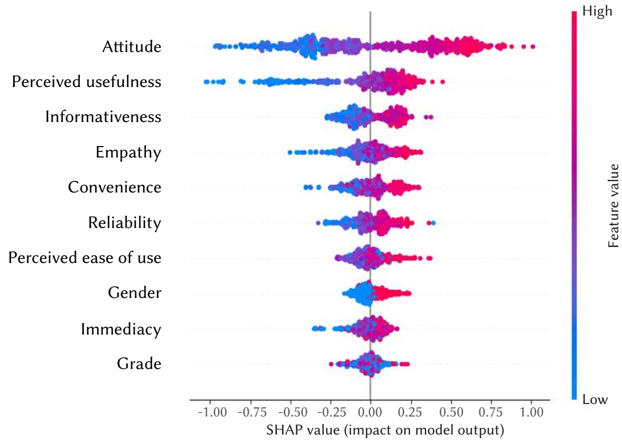


Fig. 4. SHAP summary plot of the CatBoost model
(The higher SHAP value of a feature, the higher purchase intention levels).

denotes the relative importance of each feature, with shades ranging from blue for less importance to red for greater importance, providing a clear, intuitive understanding of how each feature influences the model's predictions regarding purchase intention.

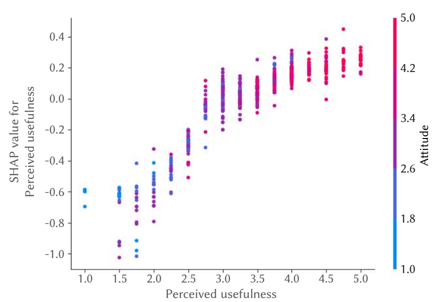
The range of negative SHAP values associated with perceived usefulness is broader, but the maximum positive SHAP value reaches only 0.5. This suggests that high perceived usefulness has a moderate positive impact on purchase intention, while low perceived usefulness significantly and negatively influences purchase intention. The impact of the remaining input variables is relatively narrow, and for the variables ranked lower, the color boundaries appear less distinct, indicating less clarity in their influence on purchase intention.

3. Variables Association Analysis

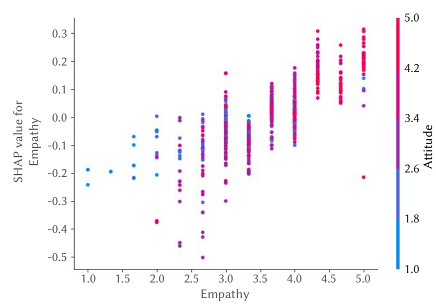
The SHAP summary plot in Fig. 4 provides a comprehensive overview of the relationship between purchase intention and the explanatory variables. To explore deeper into these relationships and their impact on purchase intention, SHAP dependency plots are employed, as illustrated in Fig. 5.

These plots detail how individual features affect the CatBoost model's predictions, with the primary y-axis showing the SHAP value of a feature and the x-axis its actual value. The secondary y-axis's color bar indicates the influence of another feature, highlighting interaction effects. These dependency plots reveal both main and interaction effects, demonstrating how features interact to influence the model's output. Notably, they explore the interactions involving the attitude feature, displaying how it interacts with other variables to impact purchase intention, with color variations representing different levels of attitude's influence.

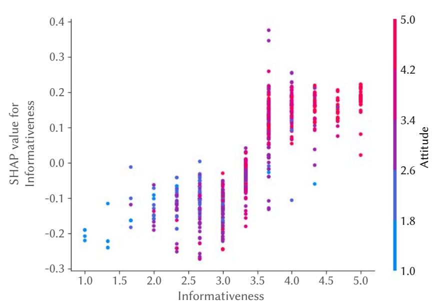
Fig. 5(a) presents the interaction between attitude and perceived usefulness. A positive SHAP value indicates high perceived usefulness and corresponds to a high attitude, displaying a clear upward trend



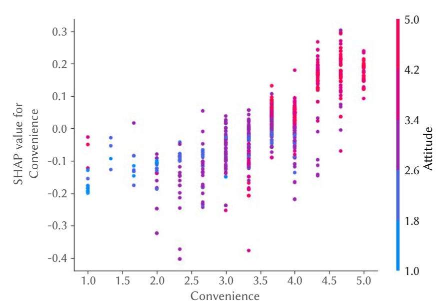
(a) Interaction between attitude and perceived usefulness



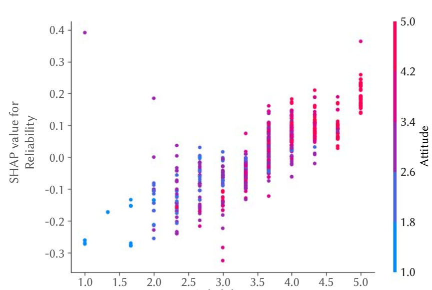
(b) Interaction between attitude and empathy



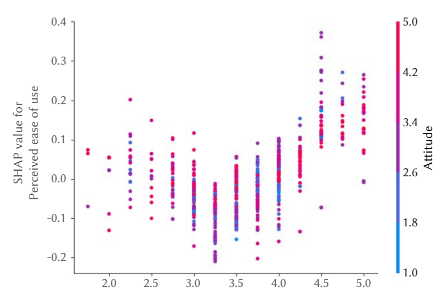
(c) Interaction between attitude and informativeness



(d) Interaction between attitude and convenience

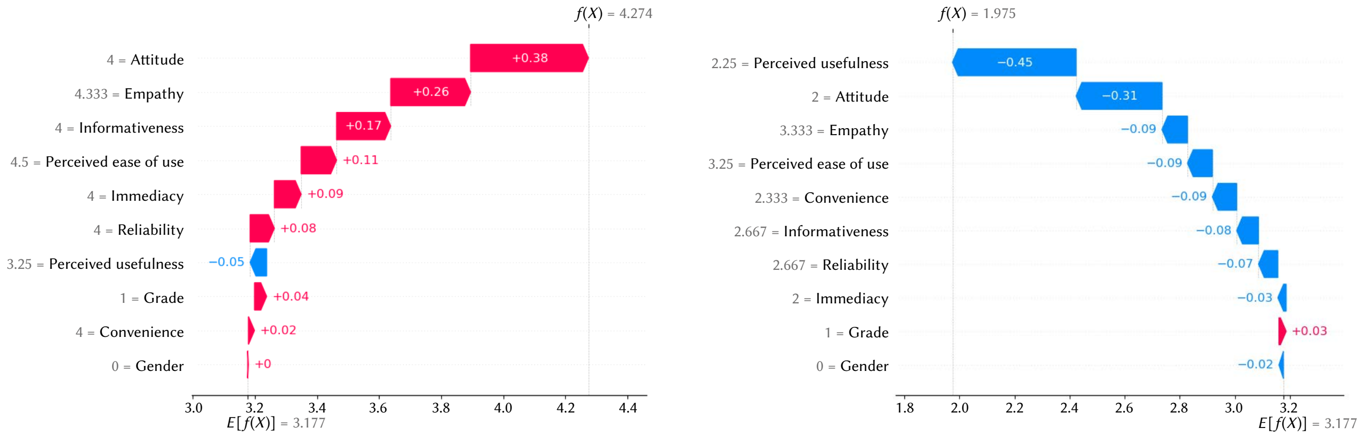


(e) Interaction between attitude and reliability



(f) Interaction between attitude and ease of use

Fig. 5. SHAP dependence plots.



(a) The sample with a high purchase intention

(b) The sample with a low purchase intention

Fig. 6. Explanation of the prediction generated by the CatBoost model using tree SHAP.

in the SHAP value as both attitude and perceived usefulness increase. Conversely, a negative SHAP value is associated with a low attitude and empathy. Figs. 5(b-e) demonstrate the interactions of attitude with empathy, informativeness, convenience, and reliability, respectively. These figures exhibit similar interaction trends to Fig. 5(a).

Fig. 5(f) illustrates the interaction between attitude and ease of use, revealing a U-shaped curve in the relationship between the SHAP value and ease of use. When the ease of use is below 3.33, the SHAP value decreases with an increase in ease of use. However, after surpassing this threshold, the SHAP value increases as the ease of use feature value rises. Notably, the distribution of attitude values lacks a distinct color boundary.

4. Individual Observation Analysis

The conventional attribute importance algorithm provides a global importance value for an attribute across the entire dataset, whereas the SHAP value offers importance values for each individual observation. Local interpretability allows us to assess how the feature values contribute to the prediction score of each observation within the sample.

Fig. 6 presents a waterfall plot based on a single observation of an individual. Fig. 6(a) illustrates the observed values of an individual from a sample with high purchase intention, while Fig. 6(b) represents one of the samples with low purchase intention. The vertical axis on the left represents the input feature and its actual value. E[f(X)] denotes the mean value of the predicted value for the target feature, while f(x) represents the predicted value of the target feature for this specific instance. In the figure, red indicates that the feature increases the purchase intention, while blue indicates that the feature decreases the purchase intention of this sample. The numbers within the arrows indicate the magnitude of influence, and the input features on the left vertical axis are ranked based on the absolute value of the magnitude of influence.

As depicted in Fig. 6(a), the mean value of the predicted purchase intention is 3.177, while the actual purchase intention value for this individual is 4.274. The difference between these two values signifies the impact of various input variables on the purchase intention. Specifically, the variables of grade (+0.04), convenience (+0.02), and gender (0) have a negligible influence on purchase intention. Conversely, perceived usefulness (-0.05), reliability (+0.08), immediacy (+0.09), and perceived ease of use (+0.11) demonstrate a slight positive impact. Moreover, informativeness (+0.17), empathy (+0.26), and attitude (+0.38) significantly contribute to the positive purchase intention.

In Fig. 6(b), the purchase intention prediction value is 1.975 for the depicted individual. For this person, grade (+0.03) demonstrates a weak positive impact. On the other hand, perceived usefulness (-0.45) and attitude (-0.31) significantly negatively impact her purchase intention. The remaining input variables exhibit negative effects with absolute values below 0.1.

Fig. 7 displays the strength of relationships among the variables. The correlation matrix highlights strong correlations between empathy and informativeness, attitude and perceived usefulness, perceived usefulness and immediacy, as well as informativeness and reliability.

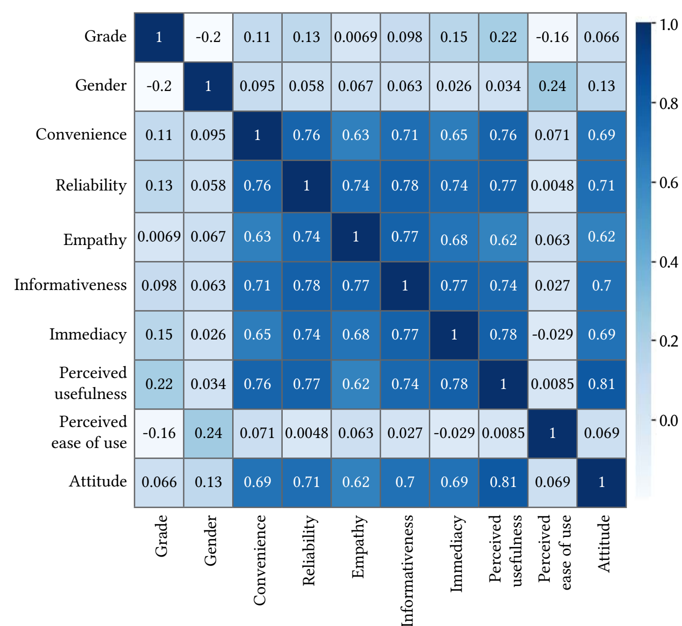


Fig. 7. Correlation matrix for the different variables.

VI. Discussion

The rapid evolution of science and technology has made consumer electrical products important for daily life, impacting communication, information access, and shopping. Consumers typically invest time in researching and comparing electronics, reflecting the tendency of buyers to conduct research before making purchase decisions [14]. With the growth of e-commerce, more consumers are choosing online platforms for their convenience and the ease of comparing products

[12]. This study focuses on identifying the main factors that influence consumer acceptance and use of e-commerce platforms to purchase consumer electrical products.

Although previous studies have extensively investigated consumers' purchase intentions on e-commerce platforms using the TAM, its application in the context of consumer electronics has been limited. Moreover, most prior research has overlooked the influence of logistics service quality (LSQ) in addressing this research question. Considering that logistics plays a crucial role in the transportation of goods between individual customers and businesses, LSQ directly affects consumers' experiences and intentions to buy online [23] [24] [91] [92].

Our findings indicate that consumers' attitudes and perceived usefulness towards online shopping, as well as the informativeness and empathy of LSQ, strongly influence their intention to purchase consumer electrical products online. Additionally, convenience, reliability, and ease of use are identified as contributing factors, although to a lesser extent. Conversely, the low importance of gender, immediacy, and grade suggests their minimal impact on consumers' purchase intention in the context of online purchases for consumer electrical products. Based on these findings, we discuss relevant theoretical and practical implications below.

A. Theoretical Implications

The findings of this study demonstrate that the majority of proposed main effects related to LSQ are relevant to purchase intention, confirming the suitability of incorporating LSQ into the TAM. Among the various drivers influencing purchase intention, attitude emerges as the most influential factor in the intention to purchase consumer electrical products online, as supported by its higher SHAP value (please refer to Fig. 3).

Attitude represents an individual's positive or negative feelings towards performing a specific behavior [68]. It is a psychological process that shapes an individual's preference or aversion towards a particular item [93]. When consumers hold positive attitudes towards a behavior, they are more likely to engage in that behavior [94]. Previous research has consistently reported positive effects of attitude on purchase intention in relation to various products (e.g., [31] [32] [33] [35] [69]).

According to Davis [65], perceived usefulness refers to "the degree to which a person believes that using a particular system would enhance his or her job performance." This factor has also been identified as a key driver of purchase intention in the context of consumer electrical products, aligning with previous studies that employed the TAM (e.g., [29] [32] [33]). However, the influence of perceived usefulness on intention can vary across different contexts. For instance, in the context of online food shopping in Vietnam, perceived usefulness strongly affects attitudes toward online food purchasing, but it does not significantly predict consumers' intention to purchase food products online [36].

In contrast, our study focuses on consumer electrical products, where perceived usefulness directly influences purchase intention. This divergence in findings may be attributed to the distinct characteristics and purposes of the products involved. Unlike electronic products, food items do not require extensive parameter comparisons, and consumers can easily gather relevant information from product packaging in offline purchases, resulting in a faster decision-making process. Moreover, consumers can find various food brands in a single physical store, whereas comparing different electronic brands is often more challenging within a single store. In summary, perceived usefulness plays a significant role in shaping consumers' purchase intention, both directly and indirectly. The higher SHAP values obtained in this experiment further support the importance of perceived usefulness in driving purchase intention.

Informativeness refers to the timeliness of logistics information [43]. Similarly, Oh et al. [42] define information quality as the extent to which overseas direct purchase platforms provide various logistics information, such as product delivery location details, to consumers. In our study, informativeness pertains to the information related to logistics provided by the platform during product delivery. Previous research has consistently highlighted the pivotal role of informativeness in online shopping decisions [95], specifically emphasizing its significant impact on consumers' online purchase behavior within the realm of logistics service quality (e.g., [42] [44]). These studies have predominantly focused on online shopping scenarios, where the merchant delivers the goods to the buyer through logistics after the buyer's payment. During this process, consumers are often concerned about the real-time location of the product, the estimated delivery time, and the convenience of the delivery schedule. Consequently, consumers of electrical products require detailed delivery information that is promptly updated.

Empathy quality encompasses the perspective of a company and its employees in providing personalized services and safeguarding customer safety and rights [45]. In our study, empathy emerges as a moderately influential factor and exerts a significant impact on consumers' purchase intention. This finding reinforces the notion that consumers' perception of a logistic company's understanding and consideration of their needs influences their decision to make an online purchase. Prior research, which regards empathy as one of the dimensions of SERVQUAL within the logistics industry, supports this conclusion [96]. Given that consumer electrical products are susceptible to damage during transportation and may be at risk of loss when stored at a pick-up point, customers expect more intimate and meticulous logistics services to mitigate these hidden risks. Thus, logistics workers need to adopt a customer-centric approach and enhance empathy in transportation and delivery processes.

Convenience and reliability are identified as contributing factors to consumers' purchase intention, albeit to a lesser extent. Informativeness, empathy, convenience, and reliability are all components associated with logistics service quality, indicating that the quality of logistics services significantly impacts consumers' willingness to purchase electrical products online. This perspective is supported by previous studies examining consumer online purchase intention [1] [25] [40] [41] [42] [43] [44] [45]. Since consumers' online purchases of electronic products rely on logistics for delivery, whether through self-operated logistics or third-party logistics, the quality of the delivery service becomes an integral part of consumers' evaluation of their online shopping experience. Considering the significant investment often associated with consumer electrical products, customers seek a reliable delivery service that ensures the protection of their valuable items from damage or loss. Consequently, a high-quality delivery service not only contributes to a satisfactory customer experience but also fosters customer retention [23]. Therefore, our findings suggest that logistics service quality should be considered as a new external variable within the framework of TAM when examining online purchases of consumer electrical products.

On the other hand, the factor of immediacy, another component of logistics service quality, has minimal impact on consumers' purchase intention in the context of online purchases for consumer electrical products. This finding contrasts with other studies that emphasize the importance of timely product receipt (e.g., [44] [45]). The discrepancy can be attributed to the specific research contexts. In the case of fresh food, consumers prioritize the freshness of the products, leading to higher quality requirements and a shorter product shelf life. As a result, consumers place greater emphasis on delivery time, the merchant's delivery capacity, and the merchant's responsiveness to return requests. In contrast, consumer electrical products do not possess stringent "shelf life" conditions, reducing consumers' urgency for timely delivery.

Furthermore, perceived ease of use has a slight effect on consumers' purchase intention online in this study. Typically, when consumers consider buying a product or adopting a technology, they prioritize its usefulness rather than its simplicity and ease of use, as suitability to their needs is paramount. Moreover, previous TAM-related studies have revealed that perceived ease of use indirectly affects purchase intention by influencing attitude [29] [32] [33] [37] or perceived usefulness [31] [33] [69] [94]. In the realm of online e-commerce, consumer behavior indicates a higher inclination towards utilizing an e-commerce platform when they perceive it as a facilitator in locating desired consumer electrical products, conducting price comparisons, and completing purchase transactions. Notwithstanding any potential complexities in platform usability, consumers exhibit a willingness to expend effort if they perceive the platform to be beneficial in addressing their needs. This may explain the limited significance of perceived ease of use for purchase intention in our study.

In conclusion, our study demonstrates that perceived usefulness, informativeness, empathy, convenience, and reliability are significant factors influencing online purchase intentions for consumer electrical products. These findings highlight the crucial role of logistics service quality in shaping consumer behavior and provide valuable insights for both academics and practitioners.

B. Practical Implications

Our findings have significant practical implications as they can provide guidelines for online electronics sellers to improve the services provided to consumers and enhance their willingness to purchase electronics online. Among the drivers of consumers' intention to purchase electronic products online, attitude and perceived usefulness emerge as two key factors. Consumers with a more positive attitude toward buying consumer electronic products (CEP) online exhibit a stronger purchase intention. To cultivate positive attitudes, e-commerce platforms need to rigorously assess the business qualifications of electronic product stores to ensure that consumers can purchase authentic products. Merchants should also exercise careful control over product quality and refrain from delivering poor-quality products to consumers.

Furthermore, consumers are more inclined to purchase CEP online when they perceive it as more useful and efficient compared to offline purchases. To facilitate this perception, platforms should provide comprehensive product parameters and explanations regarding the impact of these parameters on device functionality. Merchants should offer timely and professional pre-sales and after-sales customer service, capable of recommending suitable product models based on consumers' functional needs and budget considerations. User comments and word-of-mouth play a significant role in influencing consumers' online purchasing decisions, representing an advantage of online shopping over offline alternatives. Consumer electronics are particularly sensitive to external word-of-mouth effects, given the limitations on consumers' ability to directly experience the products. Hence, consumers often rely on reviews to avoid making erroneous purchase decisions [14]. Consequently, platforms must combat "fake reviews" to ensure the authenticity and credibility of comments, further enhancing consumers' perceived usefulness of online CEP purchases and their intention to engage in online shopping.

Moreover, e-commerce platforms should strive to improve consumers' perceived ease of use, even though its direct impact on purchase intention may be relatively modest. The individuals' perceived ease of use, as an expression of user experience, can influence their decision to accept a product or platform. This highlights the importance for online store operators and e-commerce platforms to emphasize user experience in the development of effective and user-centered platforms [46] [47]. Online store operators should optimize the display of product information and corresponding keywords to facilitate consumers' search for products aligned with their needs. The platform could incorporate a parameter comparison function module, enabling consumers to compare multiple products selected from different brand stores within the same interface.

Several LSQ factors in our study exhibited high SHAP values for purchase intention, particularly informativeness and empathy. Therefore, third-party logistics enterprises and self-operated logistics involved in fulfilling online orders for electronic products are encouraged to leverage or develop digital technologies and artificial intelligence tools, such as real-time courier positioning, to provide timely updates on delivery information and help customers understand the delivery locations. Logistics service providers should prioritize empathy by employing a larger number of employees assigned to specific clients, facilitating greater individualization and strengthening customer relationships [97]. Furthermore, service providers must adopt a customer-centric perspective and provide friendly services throughout transportation, delivery, and other stages. To enhance reliability, logistics and distribution processes associated with CEP orders should consider appropriate packaging measures to minimize the loss of electronic products during transit [98]. Additionally, proactive communication with buyers prior to delivery, confirming convenient arrangements for personal package receipt, is crucial to ensure reliable delivery and prevent loss of goods. Regarding convenience, optimizing the package layout and pickup process of post stations or express delivery cabinets, and ideally offering door-to-door delivery services, can enhance the convenience of the overall delivery experience.

In sum, this research emphasizes the pivotal roles of consumers' attitudes and perceived usefulness in shaping their intentions to purchase consumer electronic products online. For bolstering positive purchase intentions, e-commerce platforms must ensure product authenticity and maintain rigorous quality standards. Comprehensive product details and robust customer service enhance the perceived usefulness of online shopping. Additionally, specific LSQ factors, particularly informativeness and empathy, play substantial roles in influencing purchase intentions. The emphasis on empathetic and reliable logistics is further reinforced by findings in other studies [97] [98].

VII. Conclusion

Prior studies have given limited attention to examining logistics service quality within the Technology Acceptance Model (TAM) framework, particularly from a demand-side perspective. This research aims to address the gap in the literature by investigating the influence of logistics service quality on consumers' online purchases of consumer electronics products. Our study adopts an integrative approach combining TAM and logistics service quality dimensions to provide a comprehensive assessment of consumer behavior from both informational and transportation perspectives.

This study makes several contributions. First, the study integrates the TAM with logistics service quality. This research bridges the TAM framework with logistics service quality to provide a more comprehensive analysis of consumers' purchase behavior. This study highlights how individuals' acceptance of online platforms shapes their propensity to purchase consumer electronics online, given the convenience and availability of detailed product information and technical support on these channels. By considering both the information perspective and transportation perspective in purchasing consumer electronic products, the research highlights the significance of logistics service quality within the supply chain and its impact on consumers' purchase intention. Second, the research identifies influential determinants. The research identifies attitude, perceived usefulness, and informativeness as the most influential factors affecting consumers' purchase intention. By examining the impact of these factors, the research provides valuable insights into the determinants of consumers' intention to purchase electronic products online. Third, this study underscores the vital role of logistics service quality. The research emphasizes the importance of logistics service quality in the success of online retailers. It highlights the need to consider logistics service quality within the framework of TAM and discusses the challenges related to logistics service quality in the delivery of electrical products and its impact on consumers' purchase intentions. Fourth, the study employs both parametric and non-parametric analytical techniques to facilitate robust analysis of the research model. The research adopts the SHAP machine learning algorithm to analyze and interpret the impact of each variable on consumers' purchase intention. This approach enhances the transparency and interpretability of machine learning models in predicting and explaining consumers' purchase behavior. Lastly, the research offers valuable insights for both academia and practitioners by providing managerial recommendations. These recommendations enable online retailers to maintain a competitive advantage, promote successful online consumer behavior, and foster profitability in the e-commerce sector. In summary, this is the first study to synthesize the TAM and logistics service quality factors to examine consumer electronics purchase decisions in online retail, utilizing a mixed methods approach. The integration of technology acceptance and supply chain considerations provides a holistic perspective on consumer decision making, while the empirical findings provide actionable guidelines for practitioners. This research advances the field by providing a comprehensive analysis of the factors influencing consumers' purchase behavior in the context of online e-commerce platforms for consumer electronic products.

Although this study has several contributions, it also presents limitations and future work. Firstly, the generalizability of our findings to other shopping contexts may be limited as our research is specifically tailored to the online purchase of consumer electronics. To address this limitation, future studies can employ our research framework to examine the dynamics of online shopping in relation to different types of products. Secondly, while this study examines consumers' online purchase intention of consumer electrical products based on the TAM and incorporates LSQ as an external variable, we exclusively focus on the main effects proposed by TAM and exclude the examination of moderators. To enrich our understanding, future studies should explore the potential moderating effects on the proposed relationships. For instance, Wong et al. [35] discovered that perceived risk mediates the relationship between perceived usefulness and purchase intention. Conversely, Jain [32] found no moderating role of perceived risk in the relationship between attitude and intention, but identified web atmospherics as a moderator between attitude toward online shopping and online purchase intention. Future research would investigate further into complex interrelations among these factors and introduce other variables such as virtual reality shopping experiences or the role of social media influencers, thereby deepening the insight into consumer behavior concerning online purchases of electronics.

References

[1] T. Gao, "Study on the intention of foreign trade driven by cross-border E-commerce based on blockchain technology," *Security and Communication Networks*, pp.1-10, 2021.

[2] Y. Qi, X. Wang, M. Zhang, Q. Wang, "Developing supply chain resilience through integration: An empirical study on an e-commerce platform," *Journal of Operations Management*, vol. 69, no. 3, pp. 477-496, 2023.

[3] I. Masudin, E. Lau, N. T. Safitri, D. P. Restuputri, D. I. Handayani, "The impact of the traceability of the information systems on humanitarian logistics performance: Case study of Indonesian relief logistics services," *Cogent Business & Management*, vol. 8, no. 1, p. 1906052,2021.

[4] P. Kgobe, P. Ozor, "Integration of radio frequency identification technology in supply chain management: A critical review," *Operations and Supply Chain Management: An International Journal*, vol. 14, no. 3, pp. 289-300, 2021.

[5] J. Zhan, S. Dong, W. Hu, "IoE-supported smart logistics network communication with optimization and security," *Sustainable Energy Technologies and Assessments*, vol. 52, p. 102052, 2022.

[6] W. Wu, L. Shen, Z. Zhao, A. R. Harish, R. Y. Zhong, G. Q. Huang, "Internet of Everything and Digital Twin Enabled Service Platform for Cold Chain Logistics," *Journal of Industrial Information Integration*, vol. 33, p. 100443, 2023.

[7] M. Nilashi, A. M. Baabdullah, R. A. Abumalloh, K. B. Ooi, G. W. H. Tan, M. Giannakis, Y. K. Dwivedi, "How can big data and predictive analytics impact the performance and competitive advantage of the food waste and recycling industry?" *Annals of Operations Research*, pp. 1-42, 2023.

[8] M. Cotarelo, H. Calderón, T. Fayos, "A further approach in omnichannel LSQ, satisfaction and customer loyalty," *International Journal of Retail & Distribution Management,* vol. 49, no. 8, pp. 1133-1153, 2021.

[9] P. Raman, "Understanding female consumers' intention to shop online: The role of trust, convenience and customer service," *Asia Pacific Journal of Marketing and Logistics*, vol. 31, no. 4, pp. 1138-1160, 2019.

[10] M. Ramkumar, T. Schoenherr, S. M. Wagner, M. Jenamani, "Q-TAM: A quality technology acceptance model for predicting organizational buyers' continuance intentions for e-procurement services," *International Journal of Production Economics*, vol. 216, pp. 333-348, 2019.

[11] Q. Chen, N. Zhang, "Does E-Commerce Provide a Sustained Competitive Advantage? An Investigation of Survival and Sustainability in Growth-Oriented Enterprises," *Sustainability*, vol. 7, no. 2, pp. 1411–1428, 2015.

[12] Q. T. Pham, X. P. Tran, S. Misra, R. Maskeliūnas, R. Damaševičius, "Relationship between convenience, perceived value, and repurchase intention in online shopping in Vietnam," *Sustainability*, vol. 10, no. 1, p. 156, 2018.

[13] N. W. Masri, A. Ruangkanjanases, S. C. Chen, "The effects of product monetary value, product evaluation cost, and customer enjoyment on customer intention to purchase and reuse vendors: institutional trust-based mechanisms," *Sustainability*, vol. 13, no. 1, p. 172, 2020.

[14] R. Barbado, O. Araque, C. A. Iglesias, "A framework for fake review detection in online consumer electronics retailers," *Information Processing & Management*, vol. 56, no. 4, pp. 1234-1244, 2019.

[15] U. Chakraborty, S. Bhat, "The effects of credible online reviews on brand equity dimensions and its consequence on consumer behavior," *Journal of promotion management*, vol. 24, no. 1, pp. 57-82, 2018.

[16] P. Duarte, S. C. e Silva, M. B. Ferreira, "How convenient is it? Delivering online shopping convenience to enhance customer satisfaction and encourage e-WOM," *Journal of Retailing and Consumer Services*, vol. 44, pp. 161-169, 2018.

[17] M. W. A. Ghouri, L. Tong, M. A. Hussain, "Does Online Ratings Matter? An Integrated Framework to Explain Gratifications Needed for Continuance Shopping Intention in Pakistan," *Sustainability*, vol. 13, no. 17, p. 9538, 2021.

[18] U. Tandon, R. Kiran, A. N. Sah, "The influence of website functionality, drivers and perceived risk on customer satisfaction in online shopping: an emerging economy case," *Information Systems and e-Business Management*, vol. 16, pp. 57-91, 2018.

[19] D. A. Aaker, "Managing brand equity," *New York: Simon and Schuster,* 2009.

[20] Q. C. He, Y. J. Chen, "Dynamic pricing of electronic products with consumer reviews," *Omega*, vol. 80, pp. 123-134, 2018.

[21] P. Utomo, T. F. SUTRISNO, "What Influences the Online Purchasing of Electrical Equipment Products?," *KnE Social Sciences*, pp. 143-156, 2021.

[22] X. Qin, Q. Su, S. H. Huang, U. J. Wiersma, M. Liu, "Service quality coordination contracts for online shopping service supply chain with competing service providers: integrating fairness and individual rationality," *Operational Research*, vol. 19, pp. 269-296, 2017.

[23] R. Cui, M. Li, Q. Li, "Value of High-Quality Logistics: Evidence from a

Clash Between SF Express and Alibaba," *Management Science*, vol. 66, no. 9, pp. 3879–3902, 2020. doi:10.1287/mnsc.2019.3411

[24] D. Li, Y. Liu, C. Fan, J. Hu, X. Chen, "Logistics service strategies under different selling modes," *Computers & Industrial Engineering*, vol. 162, p. 107684, 2021.

[25] B. Zheng, H. Wang, A. M. Golmohammadi, A. Goli, "Impacts of logistics service quality and energy service of Business to Consumer (B2C) online retailing on customer loyalty in a circular economy," *Sustainable Energy Technologies and Assessments*, vol. 52, p. 102333, 2022.

[26] S. M. Lundberg, S. I. Lee, "A unified approach to interpreting model predictions," *Advances in neural information processing systems*, vol. 30, 2017.

[27] S. B. Jabeur, H. Ballouk, W. B. Arfi, R. Khalfaoui, "Machine learning-based modeling of the environmental degradation, institutional quality, and economic growth," *Environmental Modeling & Assessment*, pp. 1-14, 2021.

[28] L. Antwarg, R. M. Miller, B. Shapira, L. Rokach, "Explaining anomalies detected by autoencoders using Shapley Additive Explanations," *Expert systems with applications*, vol. 186, p. 115736, 2021.

[29] W. Wang, S. Wang, "Toward parent-child smart clothing: Purchase intention and design elements," *Journal of Engineered Fibers and Fabrics*, vol. 16, p. 1558925021991843, 2021.

[30] V. Chidambaram, N. P. Rana, S. Parayitam, "Antecedents of consumers' online apparel purchase intention through Virtual Try On technology: A moderated moderated-mediation model," *Journal of Consumer Behaviour*, vol. 23, no. 1, pp. 107-125, 2024.

[31] T. Zhang, W. Y. C. Wang, L. Cao, Y. Wang, "The role of virtual try-on technology in online purchase decision from consumers' aspect," *Internet Research*, vol. 29, no. 3, pp. 529-551, 2019.

[32] S. Jain, "Examining the moderating role of perceived risk and web atmospherics in online luxury purchase intention," *Journal of Fashion Marketing and Management: An International Journal*, vol. 25, no. 4, pp. 585-605, 2021.

[33] A. Xu, W. Li, Z. Chen, S. Zeng, L. A. Carlos, Y. Zhu, "A Study of Young Chinese Intentions to Purchase "Online Paid Knowledge": An Extended Technological Acceptance Model," *Frontiers in Psychology*, vol. 12, p. 695600, 2021.

[34] C. K. H. Lee, A. O. M. Wong, "Antecedents of consumer loyalty in ride-hailing," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 80, pp. 14-33, 2021.

[35] D. Wong, H. Liu, Y. Meng-Lewis, Y. Sun, Y. Zhang, "Gamified money: exploring the effectiveness of gamification in mobile payment adoption among the silver generation in China," *Information Technology & People*, vol. 35, no. 1, pp. 281-315, 2022.

[36] T. M. A. Nguyen, T. H. Nguyen, H. H. Le, "Online Shopping in Relationship with Perception, Attitude, and Subjective Norm during COVID-19 Outbreak: The Case of Vietnam," *Sustainability*, vol. 14, no. 22, p. 15009, 2022.

[37] A. Vafaei-Zadeh, T. K. Wong, H. Hanifah, A. P. Teoh, K. Nawaser, "Modelling electric vehicle purchase intention among generation Y consumers in Malaysia," *Research in Transportation Business & Management*, vol. 43, p. 100784, 2022.

[38] L. Wang, Z. Wang, X. Wang, Y. Zhao, "Explaining consumer implementation intentions in mobile shopping with SEM and fsQCA: Roles of visual and technical perceptions," *Electronic Commerce Research and Applications*, vol. 49, p. 101080, 2021.

[39] M. A. Rahaman, H. K. Hassan, A. A. Asheq, K. A. Islam, "The interplay between eWOM information and purchase intention on social media: Through the lens of IAM and TAM theory," *PloS one*, vol. 17, no. 9, p. e0272926, 2022.

[40] Y. M. Cang, D. C. Wang, "A comparative study on the online shopping willingness of fresh agricultural products between experienced consumers and potential consumers," *Sustainable Computing: Informatics and Systems*, vol. 30, p. 100493, 2021.

[41] A. H. Ali, T. Gruchmann, A. Melkonyan, "Assessing the impact of sustainable logistics service quality on relationship quality: Survey-based evidence in Egypt," *Cleaner Logistics and Supply Chain*, vol. 4, p. 100036, 2022.

[42] K. Y. Oh, S. Y. Kang, Y. G. Oh, "The Moderating Effects of Eco-Friendliness between Logistics Service Quality and Customer Satisfaction in Cross-Border e-Commerce: Evidence from Overseas Direct Purchasers in Korea," *Sustainability*, vol. 14, no. 22, p. 15084, 2022.

[43] Z. Dong, "Construction of mobile E-commerce platform and analysis of its impact on E-commerce logistics customer satisfaction," *Complexity*, vol. 2021, pp. 1-13, 2021.

[44] D. Choi, C. Y. Chung, J. Young, "Sustainable online shopping logistics for customer satisfaction and repeat purchasing behavior: Evidence from China," *Sustainability*, vol. 11, no. 20, p. 5626, 2019.

[45] Y. Jiang, P. Lai, C. H. Chang, K. F. Yuen, S. Li, X. Wang, "Sustainable management for fresh food E-commerce logistics services," *Sustainability*, vol. 13, no. 6, p. 3456, 2021.

[46] D. Winter, C. Hausmann, A. Hinderks, J. Thomaschewski, "Development of a shared UX vision based on ux factors ascertained through attribution," *International Journal of Interactive Multimedia and Artificial Intelligence*, vol. 8, no. 2, pp. 247-254, 2023.

[47] M. Schrepp, J. Kollmorgen, A. L. Meiners, A. Hinderks, D. Winter, H. B. Santoso, J. Thomaschewski, "On the importance of UX quality aspects for different product categories," *International Journal of Interactive Multimedia and Artificial Intelligence*, vol. 8, no. 2, pp. 232-246, 2023.

[48] C. W. Lu, G. H. Lin, T. J. Wu, I. H. Hu, Y. C. Chang, "Influencing factors of cross-border e-commerce consumer purchase intention based on wireless network and machine learning," *Security and Communication Networks*, vol. 2021, no. 1, pp. 1-9, 2021.

[49] J. Jia, "Analysis of alternative fuel vehicle (AFV) adoption utilizing different machine learning methods: a case study of 2017 NHTS," *IEEE Access*, vol. 7, pp. 112726-112735, 2019.

[50] J. Jia, B. Shi, F. Che, H. Zhang, "Predicting the regional adoption of electric vehicle (EV) with comprehensive models," *IEEE Access*, vol. 8, pp. 147275-147285, 2020.

[51] T. Shu, Z. Wang, L. Lin, H. Jia, J. Zhou, "Customer perceived risk measurement with NLP method in electric vehicles consumption market: empirical study from China," *Energies*, vol. 8, no. 5, p. 1637, 2022.

[52] K. Sobiech-Grabka, A. Stankowska, K. Jerzak, "Determinants of electric cars purchase intention in Poland: personal attitudes v. economic arguments," *Energies*, vol. 15, no.9, p.3078, 2022.

[53] F. Li, S. Katsumata, C. H. Lee, Q. Ye, W. D. Dahana, R. Tu, X. Li, "Autoencoder-enabled potential buyer identification and purchase intention model of vacation homes," *IEEE Access*, vol. 8, pp. 212383-212395, 2020.

[54] R. D. Borres, A. K. S. Ong, T. W. O. Arceno, A. R. Padagdag, W. R. L. B. Sarsagat, H. R. M. S. Zuñiga, J. D. German, "Analysis of Factors Affecting Purchase of Self-Defense Tools among Women: A Machine Learning Ensemble Approach," *Applied Sciences*, vol. 13, no. 5, pp. 3003, 2023.

[55] F. Taghikhah, A. Voinov, N. Shukla, T. Filatova, "Shifts in consumer behavior towards organic products: Theory-driven data analytics," *Journal of Retailing and Consumer Services*, vol. 61, p. 102516, 2021.

[56] X. Liu, X. Huang, J. Zhao, Y. Su, L. Shen, Y. Duan,... J. Guo,"Application of machine learning in Chinese medicine differentiation of dampness-heat pattern in patients with type 2 diabetes mellitus," *Heliyon*, vol. 9, no.2, 2023.

[57] H. Sahlaoui, A. Nayyar, S. Agoujil, M. M. Jaber, "Predicting and interpreting student performance using ensemble models and shapley additive explanations," *IEEE Access*, vol. 9, pp. 152688-152703, 2021.

[58] P. L. Ballester, T. D. A. Cardoso, F. P. Moreira, R. A. da Silva, T. C. Mondin, R. M. Araujo,... L. D. de Mattos Souza, "5-year incidence of suicide-risk in youth: A gradient tree boosting and SHAP study," *Journal of affective disorders*, vol. 295, pp. 1049-1056, 2021.

[59] A. A. Huang, S. Y. Huang, "Use of machine learning to identify risk factors for insomnia," *Plos one*, vol. 18, no. 4, p. e0282622, 2023.

[60] R. Fan, T. Hua, T. Shen, Z. Jiao, Q. Yue, B. Chen, Z. Xu, "Identifying patients with major depressive disorder based on tryptophan hydroxylase-2 methylation using machine learning algorithms," *Psychiatry Research*, vol. 306, p. 114258, 2021.

[61] H. Fu, "Factors influencing user usage intention on intelligent logistics information platform," *Journal of Intelligent & Fuzzy Systems*, vol. 35, no. 3, pp. 2711-2720, 2018.

[62] D. Edwards, N. Subramanian, A. Chaudhuri, P. Morlacchi, W. Zeng, "Use of delivery drones for humanitarian operations: analysis of adoption barriers among logistics service providers from the technology acceptance model perspective," *Annals of Operations Research*, pp. 1-23, 2023.

[63] C. C. Bienstock, M. B. Royne, D. Sherrell, T. F. Stafford, "An expanded model of logistics service quality: Incorporating logistics information technology," *International Journal of Production Economics*, vol. 113, no. 1, pp. 205-222, 2008.

[64] N. K. Jain, D. Kaul, P. Sanyal, "What drives customers towards mobile shopping? An integrative technology continuance theory perspective," *Asia Pacific Journal of Marketing and Logistics*, vol. 34, no. 5, pp. 922-943, 2022.

[65] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," *MIS Quarterly*, vol. 13, no. 3, pp. 319-339, 1989, doi: 10.2307/249008.

[66] Y. Liang, S. H. Lee, J. E. Workman, "Implementation of artificial intelligence in fashion: Are consumers ready?," *Clothing and Textiles Research Journal*, vol. 38, no. 1, pp. 3-18, 2020.

[67] X. Wang, W. Zhang, T. Zhang, Y. Wang, S. Na, "A study of Chinese consumers' consistent use of mobile food ordering apps," *Sustainability*, vol. 14, no. 19, p. 12589, 2022.

[68] M. Fishbein, I. Ajzen, "Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research," *Addison-Wesley*, Reading, MA, 1975.

[69] M. F. Mazzù, A. Baccelloni, S. Romani, A. Andria, "The role of trust and algorithms in consumers' front-of-pack labels acceptance: a cross-country investigation," *European Journal of Marketing*, (ahead-of-print), 2022.

[70] L. Breiman, "Random forests," *Machine learning*, vol. 45, no. 1, pp. 5–32, 2001.

[71] L. Prokhorenkova, G. Gusev, A. Vorobev, A. V. Dorogush, A. Gulin, "CatBoost: unbiased boosting with categorical features," arXiv preprint arXiv:1706.09516, 2017.

[72] T. Chen, C. Guestrin, "Xgboost: A scalable tree boosting system," Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining, pp. 785–794, 2016.

[73] A. Dasgupta, Y. V. Sun, I. R. König, J. E. Bailey-Wilson, J. D. Malley, "Brief review of regression-based and machine learning methods in genetic epidemiology: the Genetic Analysis Workshop 17 experience," *Genetic epidemiology*, vol. 35, no. S1, pp. S5-S11, 2011.

[74] A. V. Dorogush, V. Ershov, A. Gulin, "CatBoost: gradient boosting with categorical features support," arXiv preprint arXiv:1810.11363, 2018.

[75] A. Jamal, M. Zahid, M. Tauhidur Rahman, H. M. Al-Ahmadi, M. Almoshaogeh, D. Farooq, M. Ahmad, "Injury severity prediction of traffic crashes with ensemble machine learning techniques: a comparative study," *International journal of injury control and safety promotion*, pp. 1–20, 2021.

[76] W. Liang, S. Luo, G. Zhao, H. Wu, "Predicting Hard Rock Pillar Stability Using GBDT, XGBoost, and LightGBM Algorithms," *Mathematics*, vol. 8, no. 5, p. 765, 2020.

[77] G. Ke, Q. Meng, T. Finley, T. Wang, W. Chen, W. Ma, Q. Ye, T. Y. Liu, "Lightgbm: a highly efficient gradient boosting decision tree," *Adv. Neural Information Processing Systems,* vol. 30, pp. 3146–3154, 2017.

[78] P. Pornaroontham, K. Kim, S. Kulprathipanja, P. Rangsunvigit, "Water-soluble organic former selection for methane hydrates by supervised machine learning," *Energy Reports,* vol. 9, pp. 2935-2946, 2023.

[79] L. S. Shapley, "A value for n-person games," *Contribution to the Theory of games II,*vol. 28, pp. 307–317, 1953.

[80] C. Yang, M. Chen, Q. Yuan, "The application of XGBoost and SHAP to examining the factors in freight truck-related crashes: An exploratory analysis," *Accident Analysis & Prevention,* vol. 158, p. 106153, 2021.

[81] X. Jiang, H. Wang, X. Guo, X. Gong, "Using the FAHP, ISM, and MICMAC approaches to study the sustainability influencing factors of the last mile delivery of rural E-commerce logistics," *Sustainability*, vol. 11, no. 14, p. 3937, 2019.

[82] Ž. Stević, I. Tanackov, A. Puška, G. Jovanov, J. Vasiljević, D. Lojaničić, "Development of modified SERVQUAL–MCDM model for quality determination in reverse logistics," *Sustainability*, vol. 13, no. 10, p. 5734, 2021.

[83] L. A. Luyen, N. V. Thanh, "Logistics service provider evaluation and selection: Hybrid servqual–fahp–topsis model," *Processes*, vol. 10, no. 5, p. 1024, 2022.

[84] Y. K. Huang, Y. W. Kuo, S. W. Xu, "Applying Importance-performance Analysis to Evaluate Logistics Service Quality for Online Shopping among Retailing Delivery," *International Journal of Electronic Business Management*, vol. 7, no. 2, 2009.

[85] C. Fornell, D. F Larcker, "Evaluating structural equation models with unobservable variables and measurement error", *Journal of marketing research*, vol. 18, no. 1, pp. 39-50, 1981.

[86] T. H. Tsai, H. T. Chang, Y. C. Chang, Y. S. Chang, "Personality disclosure on social network sites: An empirical examination of differences in Facebook usage behavior, profile contents and privacy settings," *Computers in Human Behavior*, vol. 76, pp. 469-482, 2017.

[87] J. F. Hair, W. C. Black, B. J. Babin, R. E. Anderson, "Multivariate Data Analysis," *Pearson*, London, 2010.

[88] N. V. Chawla, K. W. Bowyer, L. O. Hall, W. P. Kegelmeyer, "SMOTE: synthetic minority over-sampling technique," *Journal of artificial intelligence research*, vol. 16, pp. 321-357, 2002.

[89] M. M. Liu, L. Wen, Y. J. Liu, Q. Cai, L. T. Li, Y. M. Cai, "Application of data mining methods to improve screening for the risk of early gastric cancer," *BMC medical informatics and decision making*, vol. 18, no. 5, pp. 23-32, 2018.

[90] L. Yao, Z. Xu, X. Zhao, Y. Chen, L. Liu, X. Fu, F. Chen, "Therapists and psychotherapy side effects in China: A machine learning-based study," *Heliyon*, vol. 8, no. 11, p. e11821, 2022.

[91] R. Hammami, Y. Frein, A.S. Albana, "Delivery time quotation and pricing in two-stage supply chains: Centralized decision-making with global and local managerial approaches," *European Journal of Operational Research*, vol. 286, no. 1, pp. 164–177, 2020.

[92] P. He, S. Zhang, C. He, "Impacts of logistics resource sharing on B2C E-commerce companies and customers,"*Electronic Commerce Research and Applications*, vol. 34, p. 100820, 2019.

[93] N. Sreen, S. Purbey, P. Sadarangani, "Impact of culture, behavior and gender on green purchase intention,"*Journal of Retailing and Consumer Services*, vol. 41, pp. 177–189, 2018.

[94] C. Hwang, T. L. Chung, E. A. Sanders, "Attitudes and purchase intentions for smart clothing: Examining US consumers' functional, expressive, and aesthetic needs for solar-powered clothing," *Clothing and Textiles Research Journal*, vol. 34, no. 3, pp. 207-222, 2016.

[95] D. Dwidienawati, D. Tjahjana, S.B. Abdinagoro, D. Gandasari, "Customer review or influencer endorsement: which one influences purchase intention more?," *Heliyon*, vol. 6, no. 11, p. e05543, 2020.

[96] J. D. German, A. K. S. Ong, A. A. N. P. Redi, K. P. E. Robas, "Predicting factors affecting the intention to use a 3PL during the COVID-19 pandemic: A machine learning ensemble approach," *Heliyon*, vol. 8, no. 11, p. e11382, 2022.

[97] K. Knop, "Evaluation of quality of services provided by transport & logistics operator from pharmaceutical industry for improvement purposes," *Transportation Research Procedia*, vol. 40, pp. 1080-1087, 2019.

[98] R. Tian, Y. Tang, "Multiobjective Planning for Logistics Distribution of Consumer Electronic Items Based on Improved Genetic Algorithm," *Wireless Communications & Mobile Computing (Online)*, vol. 2022, 2022.

[99] J. Lee, E. Suh, H. Park, S. Lee, "Determinants of users' intention to purchase probability-based items in mobile social network games: A case of South Korea," IEEE Access, vol. 6, pp. 12425-12437, 2018.

[100] M. Hu, F. Huang, H. Hou, Y. Chen, L. Bulysheva, "Customized logistics service and online shoppers' satisfaction: an empirical study," *Internet Research*, 2016.

[101] P. Christidis, C. Focas, "Factors affecting the uptake of hybrid and electric vehicles in the European Union," *Energies*, vol. 12, no. 18, p. 3414, 2019.

[102] E. C. A. Carreón, H. Nonaka, A. Hentona, H. Yamashiro, "Measuring the influence of mere exposure effect of TV commercial adverts on purchase behavior based on machine learning prediction models," *Information Processing & Management*, vol. 56, no. 4, pp. 1339-1355, 2019.

[103] S. Ghorbany, E. Noorzai, S. Yousefi, "BIM-Based Solution to Enhance the Performance of Public-Private Partnership Construction Projects using Copula Bayesian Network," *Expert Systems with Applications*, p. 119501, 2023.

[104] P. N. Ramkumar, J. M. Karnuta, H. S. Haeberle, K. A. Owusu-Akyaw, T. S. Warner, S. A. Rodeo,... R. J. Williams III, "Association between preoperative mental health and clinically meaningful outcomes after osteochondral allograft for cartilage defects of the knee: a machine learning analysis," *The American Journal of Sports Medicine*, vol. 49, no. 4, pp. 948-957, 2021.

[105] P. Wang, Z. Xu, "A novel consumer purchase behavior recognition method using ensemble learning algorithm," *Mathematical Problems in Engineering*, vol. 2020, pp. 1-10, 2020.

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