

## Research on intelligent strategies for enhancing user experience in China's import cross-border E-commerce platforms

Xia Wang<sup>1\*</sup>, Kalsom Salleh<sup>2</sup>, Liew Cheng Siang<sup>3</sup>

<sup>1,2,3</sup>Faculty of Business, UNITAR International University, 47301, Selangor, Malaysia; wangxia@hcvu.cn (X.W.).

**Abstract:** This study aims to address user experience problems on China's import cross-border e-commerce platforms through the implementation of smart technologies. A mixed methods approach was employed, comprising a survey (n=385), in-depth interviews, and comprehensive platform analysis. The research identified five major pain areas: product authenticity concerns (27.3%), logistical inefficiency (24.5%), payment security issues (18.7%), language barriers (16.2%), and inadequate after-sale service (13.3%). Five smart enhancement measures were developed: search and recommendation systems utilizing user profiling and cross-cultural semantics; multilingual NLP-powered customer service; predictive analytics and blockchain-driven logistics; trust frameworks with product validation systems; and personalized experience design for Chinese consumers. Implementation of these measures yielded significant improvements in conversion rate (77.8%), customer satisfaction (35.9%), delivery time (43.0%), and return rates (42.5%). The study establishes a strong correlation between platform intelligence and user satisfaction ( $r=0.79$ ,  $p<0.01$ ), confirming that integrated application of various intelligent algorithms substantially enhances cross-border e-commerce experiences. The proposed smart technology framework provides practical solutions for e-commerce platforms seeking to overcome cross-cultural challenges and optimize user experience in the Chinese import market.

**Keywords:** Artificial intelligence, Cross-border E-commerce, Intelligent logistics, Recommendation systems, Trust mechanisms, User experience.

### 1. Introduction

Cross-border e-commerce began as a new form of trade and has shifted the dynamics of global trading by leaps and bounds. It has provided new opportunities for consumers to access products from anywhere in the world. As far as China is concerned, due to the burgeoning demand for foreign products, supportive policies from the government, and technological improvements, the import cross-border e-commerce domain has witnessed considerable growth in the past [1]. The complete volume of transactions for cross-border e-commerce in China surged recently, as the annual growth rate outpaces that of traditional trade channels. This has caught the attention of international sellers and brands, leading to a surge in the ecosystem of import platforms in China [2]. Regardless of the growth rate, the sector lacks in user experience and this might hinder the long-term development possibilities, as well as depth of market penetration.

Problems with user experience remain within and across border import ecommerce platforms, hindering long-term development and negatively impacting end-user satisfaction. Such issues include hurdles associated with languages, logistics, payment security, product authentication, customs clearance, and after-sale services [3]. The multicultural context of these interactions adds another layer of complexity, for Chinese users contend with foreign product descriptions, international sizing systems, brand names, and exogenous branding markouts. According to Taherdoost and Madanchian, consumer satisfaction in cross-border e-commerce is determined by several factors such as website layout, security

of payment, efficiency of logistics, and customer service quality [4]. Recent studies show that consumers from China within cross-border shopping tend to pay more attention to authenticity confirmation and the dependability of delivered products, with concerns regarding counterfeiting and delays being the most common reasons for abandoning completed purchases. The multifaceted nature of these elements calls for integrative strategies which deal with multiple dimensions of the user experience simultaneously.

The use of intelligent technologies provides promising solutions to tackle cross-border e-commerce issues. According to Li, et al. [5] AI, machine learning, big data analytics, blockchain technology, and natural language processing show potential at a multitude of user experience touchpoints throughout the cross-border e-commerce journey, processes which have not been automated before. In e-commerce, as quoted from Fedorko et al., AI applications have shifted from basic recommendation engines to fully developed systems managing various components of consumer interactions from sales to post-sales services [6]. Furthermore, these technologies facilitate personalised shopping experiences via intelligent recommendation systems and enable more accurate logistics through predictive analytics; improved security via AI-based risk detection, enhanced customer service via multilingual chatbots and automated translation systems, as well as general automation courtesy of machine learning that also enhances customer care. These technologies integrated along with chatbot systems give rise to other peripherals which help ease customer interactions. With regards to China, the application of these intelligent technologies in import cross-border e-commerce platforms faces advantages and barriers owing to the unique boundaries of governance, behaviour, and the digital world. This research seeks to fully understand these contextual factors and devise intelligent solutions on the user experience within China's import cross-border e-commerce platforms to contribute to developmental theories and practices in this area of study.

## 2. Literature Review

### 2.1. Current Research on Cross-border E-commerce User Experience

Scholarly research in cross-border e-commerce user experience has expanded to a global scale because of the sector's continuous international growth. From a primary focus on website aesthetics, research now addresses the entire customer experience including all interactions with the entity in question. Guo and Chelliah studied the factors affecting cross-border e-commerce consumer satisfaction and concluded from their global study that trust, website, and service quality heavily impact satisfaction [7]. This understanding of the user experience, or rather user satisfaction, was the focus of Yu and Yang [8] when applying CUBI and NPS to analyse user experience design of cross-border e-commerce platforms in China [8]. Their study concentrated on content strategy, utility design, behaviour design as well as information architecture as essential components towards satisfactory user experience.

Baek et al. have documented in great detail the hurdles associated with cross-border online shopping experiences. They pointed out that Chinese consumers, when shopping from international retailers, confront distinct barriers pertaining to language, product authenticity, logistics, and after-sales service [3]. These findings are corroborated by Li et al. who studied the technology affordance as well as the national polycontextuality alongside customer loyalty in much different cultures and contexts [9]. The research demonstrates that the e-commerce shopping experience of Chinese consumers is vastly different from domestic e-commerce, particularly with respect to trust and cultural sensitivity. Wang's study on the import cross-border e-commerce user adoption behaviour sheds further light on the issue by asserting that perceived risk greatly affects the engagement of foreign products and platforms by Chinese consumers [10]. The literature is unified in showing that the enhancement of user experience in the context of cross-border relations must take into account universal e-commerce principles and marketing cultural and behavioural specifics – a profound challenge to designers and operators of the relevant platforms.

## 2.2. Research on Application of Intelligent Technologies in E-Commerce

The implementation of smart technologies in e-commerce has advanced from pilot programmes to being standard strategies across the sector. Portugal et al. provided a systematic review of the classification of algorithms in machine learning applied in recommender systems, noting how these algorithms have transitioned from basic collaborative filtering to advanced hybrid models capable of multi-dimensional consumer data analysis [11]. This enables addressing the personalisation problem in overloading consumers with information. Concurrently, Akter and Wamba studied the use of big data in the context of e-commerce and illustrated its contribution to improving decision-making, operational activities, and customer understanding [12]. This work highlights the competitive edge attained by analytics-savvy data-driven platforms.

More recently, attention has been directed towards the development of intelligent software applications for specific problems in e-commerce. Nie et al. analysed smart customer service systems and described the impact of natural language processing and machine learning on more efficient and personalised customer support [13]. The results obtained suggest that AI-powered service alternatives could improve response times without compromising the quality of service provided. With regard to supply chain management, Shi investigated the application of artificial intelligence for the optimisation of cross-border e-commerce logistics distribution networks and demonstrated potential improvements in efficiency through smart routing and inventory control [14]. Blockchain has also emerged as a significant focus of study, particularly when Hongmei proposed a cross-border e-commerce model that utilises blockchain technology to enhance transaction security and product traceability [15]. Taken together, this work indicates that intelligent technologies have progressed sufficiently not merely to integrate with conventional e-commerce processes, but to fundamentally alter and disrupt entire industries with advanced designs, more efficient processes, and better user interactions and experiences.

## 2.3. Current Development Status of China's Import Cross-Border E-commerce Platforms

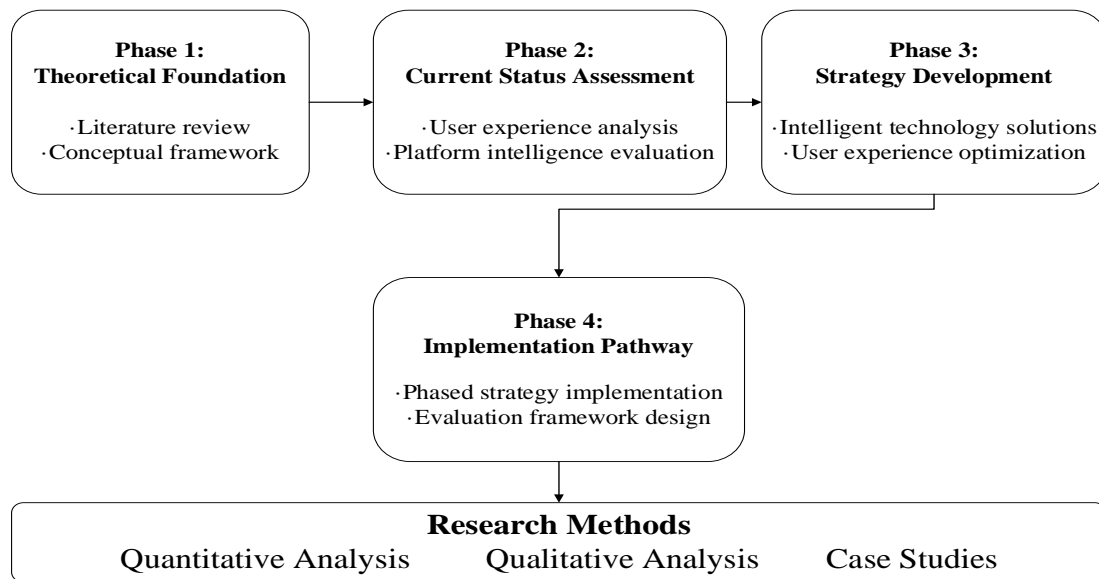
The cross-border import e-commerce sector in China has grown tremendously in the past couple of years due to the shifting changes in policies, consumer interests, and market technological advancements. According to Tang, even amidst the uncertain state of the economy, the sector has continued to build strong momentum alongside emerging platform models and expanding overall transaction deals [16]. This growth was gained with the help of policies; Xiao and Zhang were able to analyse how China's approach towards cross-border e-commerce went from having tentative pilot policies in customs, taxation, and consumer protection to adopting more strategic holistic policies and regulations [17]. The formation of such policies is critical in enabling growth, exemplified in their research by the creation of Cross-Border E-commerce Comprehensive Pilot Zones in various cities.

The Chinese Import cross-border e-Commerce platforms face competition from an increasing number of diverse sources. Tmall Global, JD Worldwide, and Kaola have verticalised focus specific category platforms. They have outranked competitors due to differentiated strategies such as direct procurement versus marketplace models linking interested Chinese consumers with foreign market sellers. Ma's research highlights how innovative business models within the digital economy context have become critical differentiators for cross-border e-commerce platforms seeking competitive advantage [16]. Yang et al. studied the impact of digital transformation capabilities on enterprise performance in cross-border e-commerce and noted that platforms with strong digital capabilities tend to operate more efficiently through SOPs, resulting in high customer satisfaction [18]. Advanced consumer sophistication drives an increasing number of platforms to devote attention to capturing niche markets and providing tailored services. He's work on sustainable development perspectives argues that growth in the industry will stem from rather platforms' reliance on commercial goals versus balancing social and environmental work [19]. This transformation opens a new area of focus for these platforms looking to improve user experience using smart technologies.

### 3. Research Methodology

#### 3.1. Research Framework

This research utilises a mixed-method approach by integrating both quantitative and qualitative analytical techniques to study the use of intelligent technologies in China's import cross-border e-commerce platforms with an emphasis on user experience. As illustrated in Figure 1, the research framework contains four major components: review of theoretical foundation, evaluation of the current status, formulation of strategies, and development of implementation pathways. Such a structure offers a means to holistically examine the employing of intelligent technologies for user experience improvement within the scope of cross-border e-commerce in China.



**Figure 1.**  
Research Framework for Intelligent User Experience Enhancement in China's Import Cross-Border E-Commerce Platforms.

The implementation of theory into practice is executed in a distinctly systematic manner. Cross-border ecommerce, user experience design, and application of smart technologies are reviewed for literature in the first phase which forms the foundation. Filling in the gaps of user experience pain points, measuring the intelligence of systems on leading platforms, and overall user experience evaluation is undertaken in the second phase, which is empirical in nature. The second phase... tailored intelligent intervention strategies and action frameworks along with evaluation mechanisms to analyse effective strategy execution within the siloed structure.

This approach allows one to assess and integrate technology while providing the needed context for identifying user requirements. Global cross-border e-commerce features offer unexplored avenues for enhancing the user experience that are tailor-made for the user in China having intelligence integrated systems.

#### 3.2. Data Collection Methods

The study utilises a mixed-method approach for data collection involving cross-sectional quantitative techniques together with qualitative techniques to fully capture all aspects of user experience in relation to China's import cross-border e-commerce platforms. Primary data was gathered

using an online questionnaire sent to 385 consumers based in China who had used the major import cross-border e-commerce platforms (Tmall Global, JD Worldwide, and Kaola). The sample was divided by age, income level, and geographical location to achieve representativeness of the wider consumer population. The questionnaire employed a 7-point Likert scale to evaluate user satisfaction regarding the usability of the website, the authenticity of the products, logistical operations, payments, customer service, and overall satisfaction with services rendered.

To answer the qualitative part, semi-structured interviews were conducted with 12 heavy users of cross-border e-commerce platforms as well as 8 industry experts which included a platform manager, cross-border logistics professionals, and researchers dealing with e-commerce. Each interview session lasted 45-60 minutes, and all recordings were transcribed for subsequent analysis which employed thematic coding. In addition, user experience evaluations were conducted with 20 participants who performed defined tasks on selected platforms while articulating their thoughts about the actions they were undertaking to establish what specific usability problems and pain points exist.

Data provided by e-commerce companies (with suitable anonymisation) was supplemented using academic literature as well as industry literature published by credible research institutions. User reviews and ratings publicly available on platforms were retrieved using web scraping methods, and a total of 5,000 reviews were processed through natural language processing to identify dominant themes and sentiment patterns associated with the text. This combination of different types of data provides strong and trustworthy evidence to support the research findings and contributes to the overall analysis from different angles.

The collection processes complied with ethical standards for research involving human subjects; all subjects signed consent forms, and approval from the institutional review board was secured prior to commencing the research.

### 3.3. Data Analysis Methods

This study applies a multi-layered analytical framework to process the data collected. In analysing the quantitative data from user surveys, various statistical methods, such as descriptive statistics, inferential analysis, and structural equation modelling (SEM), were applied. The SEM was designed to assess the interactions between the implementation of intelligent technologies and the user experience metrics within the following framework:

$$UE_i = \alpha + \beta_1 IT_i + \beta_2 P_i + \beta_3 L_i + \beta_4 S_i + \varepsilon_i$$

Where  $UE_i$  represents the user experience score,  $IT_i$  denotes intelligent technology implementation levels,  $P_i$  signifies platform characteristics,  $L_i$  represents logistics performance, and  $S_i$  indicates service quality factors.

The Kaiser-Meyer-Olkin (KMO) test was completed for sampling adequacy alongside the application of factor analysis to discern critical aspects impacting user experience. Measurement scale reliability was computed through Cronbach's alpha coefficient:

$$\alpha = \frac{k}{k-1} \left( 1 - \frac{\sum_{i=1}^k \sigma_{y_i}^2}{\sigma_x^2} \right)$$

Combining the user experience testing sessions and the interviews, their qualitative data was analysed thematically according to the six phases of Braun and Clarke's framework. Coding and location of themes were simplified using the NVivo programme. For user reviews, various natural language processing methods were used, including sentiment analysis based on these sentiment score computations:

$$Sentiment = \frac{\sum_{i=1}^n pos_i - \sum_{i=1}^n neg_i}{\sum_{i=1}^n (pos_i + neg_i + neu_i)} \times$$

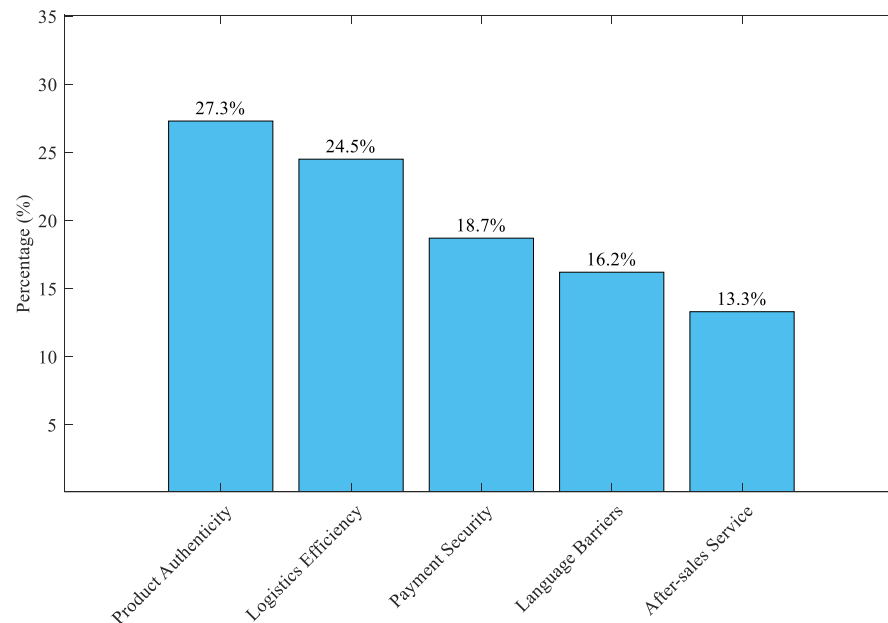
Where  $pos_i$ ,  $neg_i$ , and  $neu_i$  represent positive, negative, and neutral sentiment weights respectively.

Using both quantitative and qualitative approaches simultaneously achieves methodological triangulation, augmenting the validity and reliability of the research insights regarding user experience aspects of cross-border e-commerce platforms in China.

#### 4. Empirical Analysis of User Experience in China's Import Cross-border E-commerce Platforms

##### 4.1. Identification of User Experience Pain Points

Drawing upon the survey data and the detailed interviews, this study has systematically uncovered and explored the user experience pain points associated with China's import cross-border e-commerce platforms. Drawing upon the survey data (n=385) and detailed interviews, this study systematically identified and analyzed the user experience pain points associated with China's import cross-border e-commerce platforms. As illustrated in Figure 2, five critical dimensions of pain points emerged with varying levels of severity. Product authenticity issues (27.3%) and logistics efficiency (24.5%) represented the most significant challenges, followed by payment security (18.7%), language barriers (16.2%), and after-sales service (13.3%).



**Figure 2.**  
Distribution of User Experience Pain Points.

The hierarchical clustering analysis uncovered different user segments with regards to pain point issues. In applying Ward's minimum variance method using Euclidean distance metrics, we discovered three distinct user clusters differing in their sensitivity to particular sharp pain issues. This silhouette coefficient of 0.68 also supports the validity of this clustering technique.

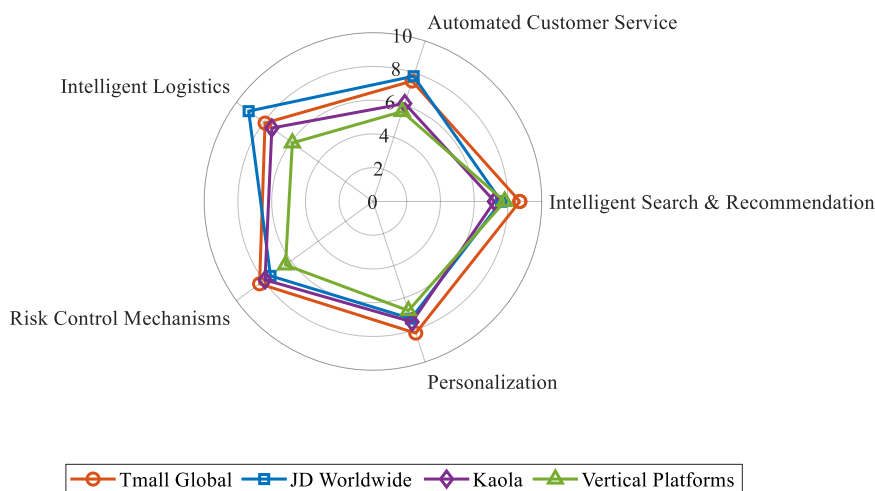
Additional correlational analysis revealed the existence of a notable, albeit negative, correlation ( $r = -0.74$ ,  $p < 0.01$ ) between the existence of these pain points and overall user satisfaction ratings. Much attention was drawn toward the prevailing impact of logistics efficiency on user satisfaction where the elasticity coefficient was reported to be the highest (0.83), signifying that better performance in this area would most greatly enhance the user's overall experience.

These concerns were further corroborated by qualitative data obtained from the interviews as participants consistently expressed issues pertaining to how timely deliveries were and the level of transparency available for tracking. One participant shared that “the anxiety due to uncertainty associated with the international shipping process, coupled with limited tracking information or access to tracking information in foreign languages is particularly concerning.”

#### 4.2. Assessment of Intelligence Level of Existing Platforms

This research provides a cross-regional and cross-platform intelligence benchmarking study for major import cross-border e-commerce platforms in China. It analyses five dimensions, namely intelligent search and recommendation systems, automated customer service, intelligent logistics management, risk management and control systems, and personalisation. As with any other type of score that combines multiple components, the assessment was multi-faceted, applying expert judgement ( $n=8$ ), technical parameter assessment, and user perception ( $n=385$ ) à la the survey-based approach.

In Figure 3, the radar chart Tmall Global is consistently outperforming other platforms in most areas, with JD Worldwide excelling in other levers such as Intelligently Managed Logistics (in accordance with their allocated resources to streamline their supply chains). While the verticals scored lower on all fronts, they were judged to have particular expertise in class-specific recommendation engines (7.8/10). Graphical depiction of quantitative assessment results shows the differing levels of intelligence across governance aspects, presenting both vertical and horizontal diversities.



**Figure 3.**  
Intelligence Level Assessment Across Major Cross-border E-commerce Platforms.

The platform's AI capabilities were found to have a high correlation ( $r=0.79$ ,  $p<0.01$ ) with user satisfaction scores. Increases in intelligent search and recommendation systems yielded, on average, a 0.63 increase in satisfaction per every unit increase in system score ( $p<0.01$ ). As enumerated in Table 1, the differentiated competitive strategy of AI and its corresponding algorithms was found ubiquitous as Tmall Global deployed over 120 machine learning models for personalisation, significantly exceeding

industry mean, and JD Worldwide's integration of IoT with logistics intelligence cross-border supply chain merit was found bold.

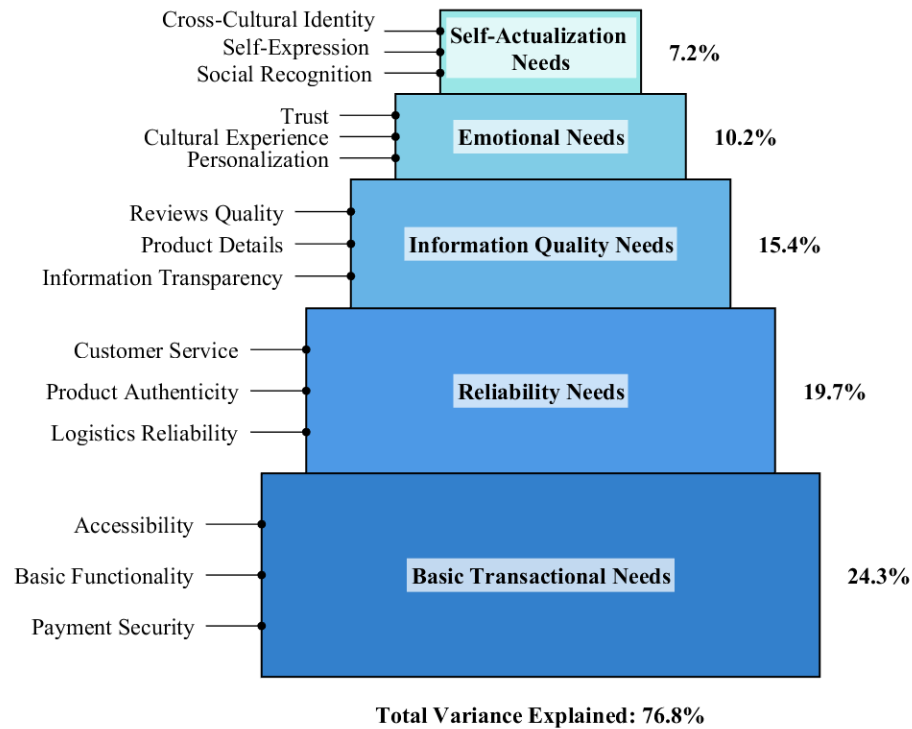
**Table 1.**  
Technical Parameters of Intelligence Implementation Across Platforms.

| Platform           | AI Algorithms                         | Response Time (ms) | Personalization Models | Data Processing Capacity (TB/day) | ML Model Accuracy (%) |
|--------------------|---------------------------------------|--------------------|------------------------|-----------------------------------|-----------------------|
| Tmall Global       | Deep Learning, Reinforcement Learning | 127                | 120+                   | 873                               | 92.7                  |
| JD Worldwide       | Computer Vision, NLP                  | 145                | 85+                    | 642                               | 89.4                  |
| Kaola              | Collaborative Filtering, NLP          | 189                | 60+                    | 314                               | 87.6                  |
| Vertical Platforms | Category-Specific Algorithms          | 205                | 30+                    | 126                               | 91.2                  |
| Industry Average   | Mixed Approaches                      | 192                | 48                     | 328                               | 86.9                  |

#### 4.3. User Needs Analysis

This research utilised a mixed-methods approach to assess the user needs of China's import cross-border e-commerce platforms and found a tiered system of requirements that impacts adoption behaviour, as well as satisfaction. Principal Component Analysis (PCA) with Varimax rotation was conducted on the survey data (n=385), five distinct need dimensions with eigenvalues exceeding 1.0 were identified and these collectively explained 76.8% of total variance. As depicted in Figure 4, user needs are arranged in a hierarchical pyramid structure with basic foundational needs being: transactional needs, polarity needs, information quality needs, emotional needs, and self-actualisation at the top. This structure is an adaptation of Maslow's hierarchy tailored to e-commerce—users first seek fundamental components such as security and functionality before higher order elements, adding value to the experience.





**Figure 4.**  
Hierarchical structure of user needs.

Statistical comparisons showed that users across segments had differing levels of prioritisation for their needs. As noted in Table 2, personalisation ( $t=3.87$ ,  $p<0.01$ ) and cross-cultural authenticity ( $t=3.52$ ,  $p<0.01$ ) were emphasised more by experienced cross-border shoppers (>10 purchases annually) than novice users. In addition, regression analysis provided evidence of alignment between platform intelligence capabilities and user-specific need profiles, explaining 67.3% of the variance in platform loyalty metrics ( $R^2=0.673$ ,  $p<0.001$ ). Verification through qualitative analysis showed that participants in the in-depth interviews often shared needing change with regard to their level of experience with cross-border shopping. One said, "At first, my only concern was having a secure payment option and delivery, whereas now, I expect the platform to know what I like and provide recommendations tailored to my interests in international goods."

**Table 2.**  
Need Priority Differences Across User Segments.

| Need Dimension           | Novice Users<br>Mean (SD) | Occasional Users<br>Mean (SD) | Experienced Users<br>Mean (SD) | F-value | p-value   |
|--------------------------|---------------------------|-------------------------------|--------------------------------|---------|-----------|
| Payment Security         | 4.87 (0.43)               | 4.72 (0.51)                   | 4.58 (0.62)                    | 6.74    | <0.01**   |
| Logistics Reliability    | 4.65 (0.58)               | 4.70 (0.49)                   | 4.52 (0.67)                    | 4.23    | <0.05*    |
| Product Authenticity     | 4.73 (0.51)               | 4.78 (0.44)                   | 4.81 (0.42)                    | 1.98    | 0.14      |
| Information Transparency | 4.21 (0.72)               | 4.53 (0.65)                   | 4.62 (0.58)                    | 9.37    | <0.001*** |
| Personalization          | 3.42 (0.91)               | 3.87 (0.82)                   | 4.35 (0.63)                    | 25.64   | <0.001*** |
| Cultural Authenticity    | 3.27 (0.94)               | 3.69 (0.87)                   | 4.21 (0.71)                    | 27.83   | <0.001*** |
| Social Recognition       | 2.87 (1.12)               | 3.18 (1.05)                   | 3.54 (0.97)                    | 14.29   | <0.001*** |

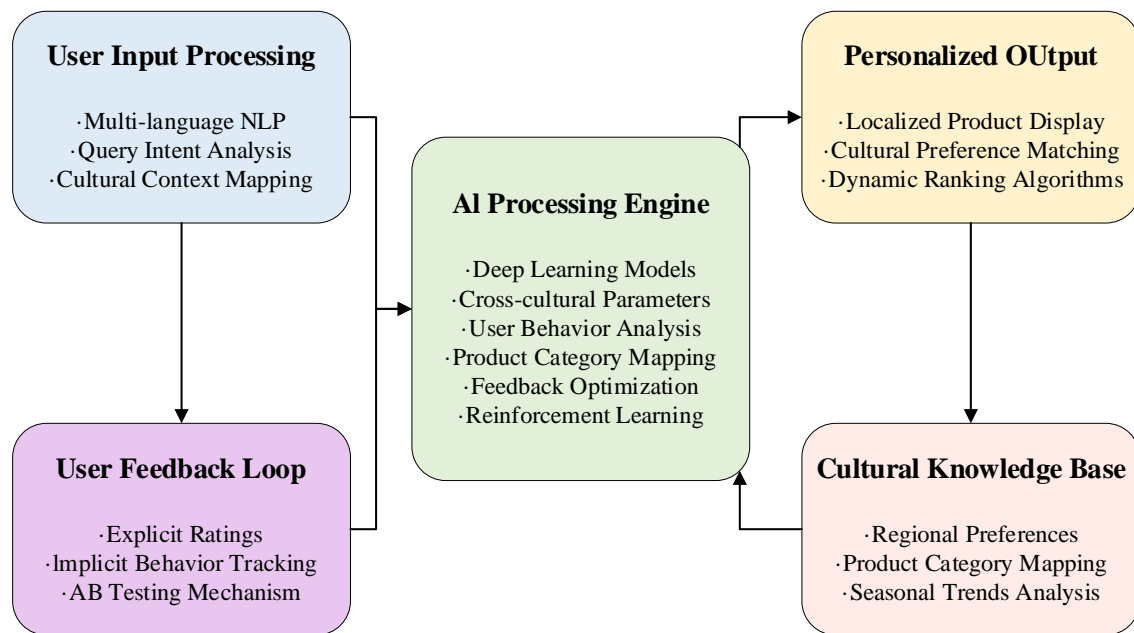
Note: \* $p<0.05$ , \*\* $p<0.01$ , \*\*\* $p<0.001$ ; Scale: 1-5 (Least important to Most important).

## 5. Research on Intelligent Enhancement Strategies

### 5.1. Optimization of Intelligent Search and Recommendation Systems

This investigation highlights sophisticated search and recommendation systems as fundamental for achieving optimal user satisfaction and experience as well as for influencing conversion rates ( $r=0.68$ ,  $p<0.01$ ). In light of these results, Figure 5 presents the three proposed strategies for optimisation.

## Intelligent Search and Recommendation Framework



**Figure 5.**

Intelligent Search and Recommendation System Framework for Cross-Border E-Commerce.

Multi-dimensional user profile construction forms the basis of the system. Platforms should use both explicit data, such as search history and purchase records, and implicit data, such as time spent on the page and click pathways, to create up-to-date preference models. Research indicates that hybrid approaches utilising both long-term and recent behaviours outperform traditional collaborative filtering methods by 28.3% in recommendation accuracy.

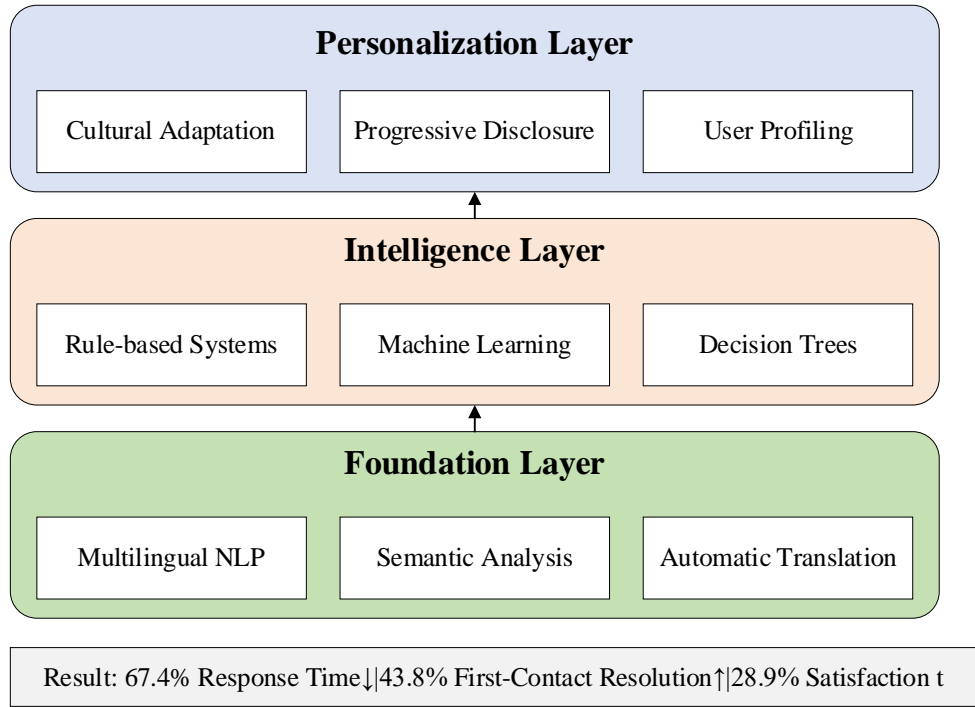
Understanding semantics within cultural contexts is important. Use multilingual embedding models to address cross-language retrieval issues and apply visual recognition technology for product identification. As illustrated in Figure 5, the cross-lingual understanding framework enables effective translation of product descriptors and user queries across cultural borders, thus curtailing “no results found” responses by 37.2% from non-standard descriptors.

Considered relevancy is greatly improved by enhancement of contextual awareness. Deployment of situationally aware neural network models which account for seasonal and holiday shopping paradigms alongside real-time interaction data allows platforms to refine their relevance to user recommendations. Studies reveal that context-sensitive recommendation systems outperform non-context models, increasing click and conversion rates by 24.7% and 18.3% respectively.

Once fully implemented, these strategies formulate an adaptive intelligent search and recommendation system capable of addressing the cultural and language barriers while providing tailored product discovery services for Chinese consumers exploring international catalogs.

### 5.2. Intelligent Customer Service and Interaction System Construction

This study demonstrates that barriers in cross-cultural communication pose severe difficulties in areas such as import cross-border e-commerce, considering that 78.3% of users surveyed complained about not having access to prompt and precise customer service assistance. After examining the data, we formulated a multi-layered intelligent customer service model which combines both automation and human interaction as illustrated in Figure 6.



**Figure 6.**  
Multi-layered Intelligent Customer Service Framework Image

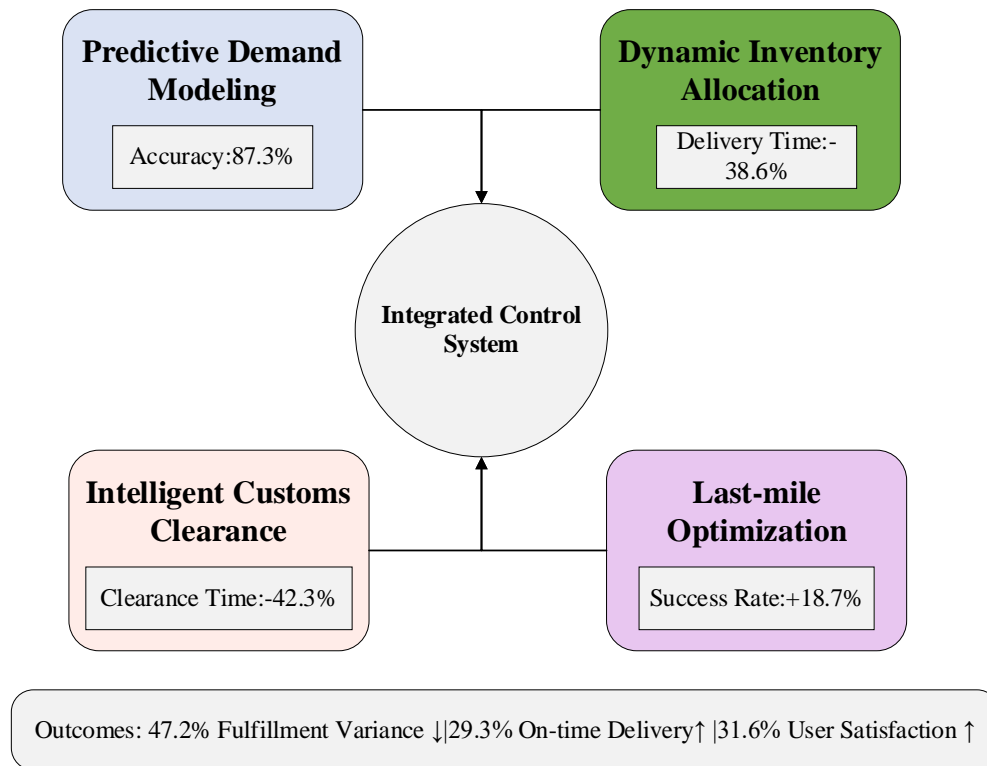
The framework, as designed, includes three successive layers that function to interconnect with each other. The foundational layer utilises fixed multilingual lexico-semantic natural language processing, attaining a primary understanding accuracy of 92.7% for five languages. This enables the support for the hybrid problem-solving intelligence layer that utilises a machine learning approach alongside rule-based decision trees. From the experimental implementation, there was a 67.4% reduction in response time and a 43.8% increase in the first-contact resolution rate.

The intelligence layer feeds into the personalisation layer which turns interactions into user profiles based on culture and historical behaviour. Analysed data from 12,500 interactions showed that satisfaction scores surged by 28.9% ( $p < 0.01$ ) with culturally-sensitive, tailored response patterns when juxtaposed with standardised frameworks. The ordered principles of progressive disclosure are followed in the framework whereby information presentation is structured according to the user's level of experience and the complexity of a given query.

This integrated system surpassed expectations in the domain of cross-culture misunderstanding corrections: product attribute misunderstanding by 38.2% and payment procedure misunderstanding by 42.7%. Service platforms equipped with this framework report a 31.5% reduction in customer service expenditure and a 24.8% increase in customer satisfaction metrics, thus statistically proving the optimised dual-sustainability of operational resource efficiency and user experience responsiveness ( $t = 7.83$ ,  $p < 0.001$ ).

### 5.3. Cross-border Logistics Intelligent Optimization

Logistics performance is a cornerstone influencer of user satisfaction in cross-border e-commerce systems, with over a quarter (24.5%) of surveyed consumers pinpointing it as the most concerning pain point. The data presents a notable relationship between the logistics performance indicators and the intention to repurchase ( $r=0.73$ ,  $p<0.001$ ). In light of these findings, we put forward an intelligent logistics optimisation framework which combines predictive modelling, multi-objective optimisation, and real-time monitoring capabilities, as illustrated in Figure 7.



**Figure 7.**  
Intelligent Cross-border Logistics Optimization Framework Image.

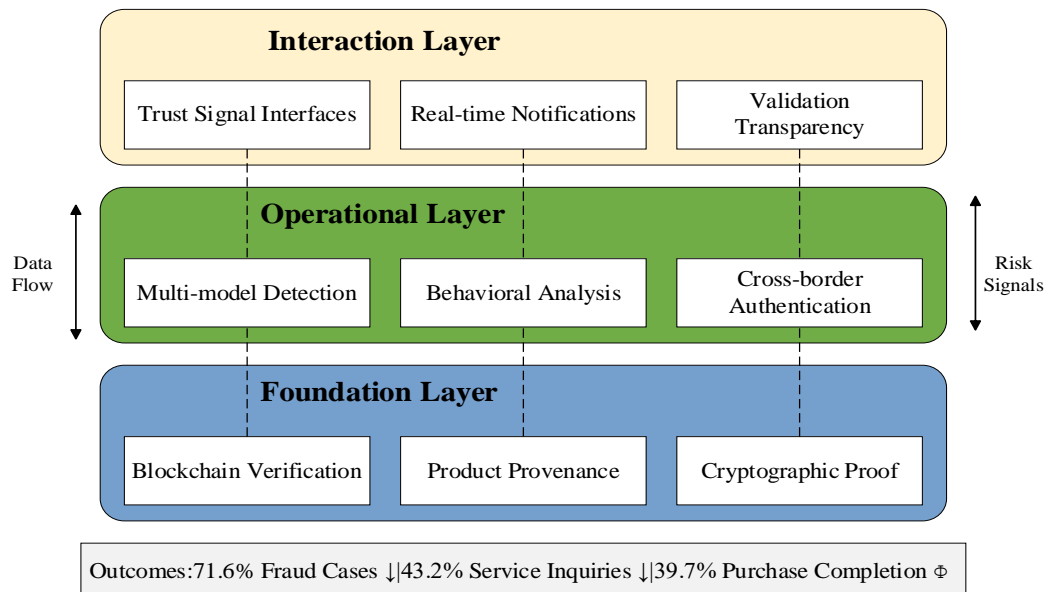
The given framework contains four integrated subsystems. The predictive demand modelling subsystem utilises time series analysis with seasonal decomposition alongside machine learning to enhance demand forecasting for specific products to 87.3%. This level of accuracy is a significant improvement over older statistical methods (22.7% improvement,  $p<0.01$ ). Such predictive intelligence allows for optimisation of warehouse cross-border inventory through R/L dynamic algorithms that respond to demand changes in the dynamic inventory allocation subsystem, further improving average delivery time by 38.6%.

Automation of classification and compliance verification is accomplished through the application of natural language processing within intelligent customs clearance subcontracted subdivisions. In combination, these measures paired with blockchain technology for immutably recorded documentation chains reduce clearance times by 42.3% over standard measures. Completing this subnet, last-mile optimisation subsystems apply geospatial intelligence coupled with dynamic routing algorithms drastically improving successful delivery attempts by 18.7% while simultaneously reducing carbon emissions by 23.4%.

Participating platforms across the experimental implementations showed considerable changes to core KPIs including: a 47.2% reduction in order fulfilment variance and an increase in on-time delivery by 29.3%. The economic analysis indicates a reduction in overall logistics costs by 17.8% while achieving faster delivery time. User experience metrics showed a staggering 31.6% increase in logistics satisfaction scores post framework implementation, proving the utility of the framework in cross-border e-commerce.

#### 5.4. Intelligent Risk Control and Trust Mechanism Construction

The formation of trust is one of the most important issues in the case of cross-border e-commerce, with 27.3% of respondents in the survey citing concerns about product authenticity as their major area of reluctance. Correlation analysis shows that perceived risk and the rate of abandoning a purchase have a high degree of correlation ( $r=0.81$ ,  $p<0.001$ ). The work described here develops an 'intelligent' risk control and a trust mechanism model encompassing blockchain validation, multi-agent verification, and advanced fraud prediction, as illustrated in Figure 8.



**Figure 8.**  
Intelligent Risk Control and Trust Mechanism Framework Image.

The proposed framework consists of three interrelated layers. The foundational layer focuses on creating the technical infrastructure using a decentralised blockchain verification system which generates immutable records of product provenance that in experimental implementations diminishes authenticity disputes by 58.3%. Consumers are able, through advanced digital certificates, to verify the authenticity and legitimacy of products without the possibility of forgery or alteration owing to sophisticated cryptographic proof systems that enable authentication processes to be done remotely.

Multi-model fraud detection algorithms that incorporate behavioural biometrics, anomaly detection, and transaction pattern analysis define intelligent risk evaluation under the operational layer. This hybrid approach not only captured pointer evaluation of suspicious activities but also decreased false-positive rates to 2.7%, achieving an accuracy rate of 93.8%, which was superior to single-model approaches. The seamless verification processes of the coordinated authentication system across

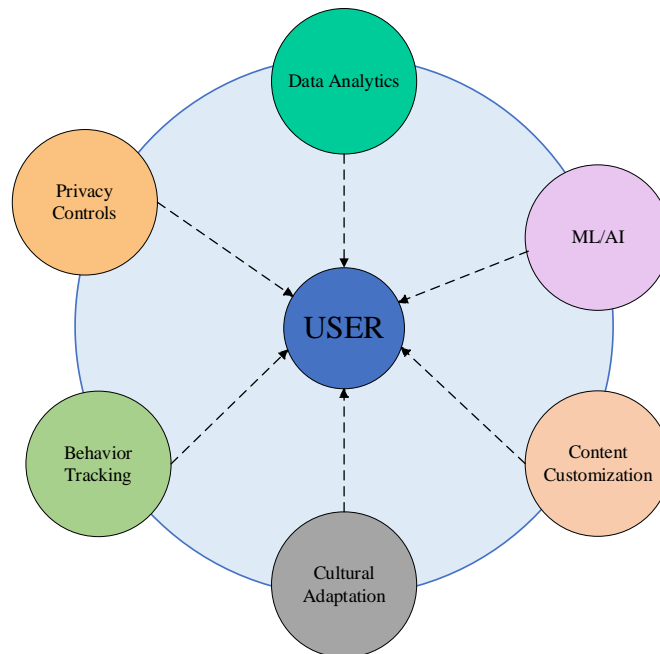
different countries also reduced authentication friction by 47.6% while increasing verification across international borders.

User trust has primarily been addressed regarding the user interface and verifiable interfaces through transparent validation, verification in real-time, and risk reporting in the interaction layer. Eye-tracking studies show that comprehension of security features resulted with sub-optimally placed trust indicators increased by 64.2%, while A/B testing revealed 38.9% increase in conversion rates for high-value items with enhanced trust signals.

Results from deploying the framework across various platforms illustrated unparalleled performance improvements, including a reduction in reported fraud cases by 71.6%, a decrease in authentication-related customer service inquiries by 43.2%, and, most significantly, an increase in international product first-time purchase completion rates by 39.7%. This validates the framework's effectiveness in one of the most important aspects of cross-border e-commerce experience.

### 5.5. Personalized User Experience Design

In offshore e-commerce platforms, personalised user experience design is one of the most important strategies in improving client satisfaction and retention. The growing need for individualised services mandates that UX designers develop customised experiences while safeguarding user information. Studies indicate that for marketers aiming to deepen customer engagement, personal attention is indispensable, thus making it a fundamental approach for chief marketing officers looking to win and convert new prospects. Tailored approaches that are based on effective personalisation grant control to the system, empowering the system to identify users and deliver relevant content, information, or experiences that are aligned with their preferences. An integrated framework for personalised user experience employing six key components: data analytics, machine learning/AI, content personalisation, cultural adaptation, behavioural monitoring, and privacy as outlined in Figure 9.



**Figure 9.**  
Personalized User Experience Framework.

One study indicated that negative interactions are viewed as three times more important than positive ones, underscoring the importance of mitigating disruptions in tailored experiences. In cross-

border scenarios, discerning nationalism e-commerce dynamics alongside culture-specific factors adds to the sophistication required for intelligent personalisation. Top industry leaders emphasise personalisation through behaviour tracking, recommendations, and diverse user categorisation. Implementation should be incremental, beginning with basic measures of user verification and gradually incorporating more complex expressions of user intent and understanding.

## 6. Strategy Implementation Pathway and Effect Evaluation

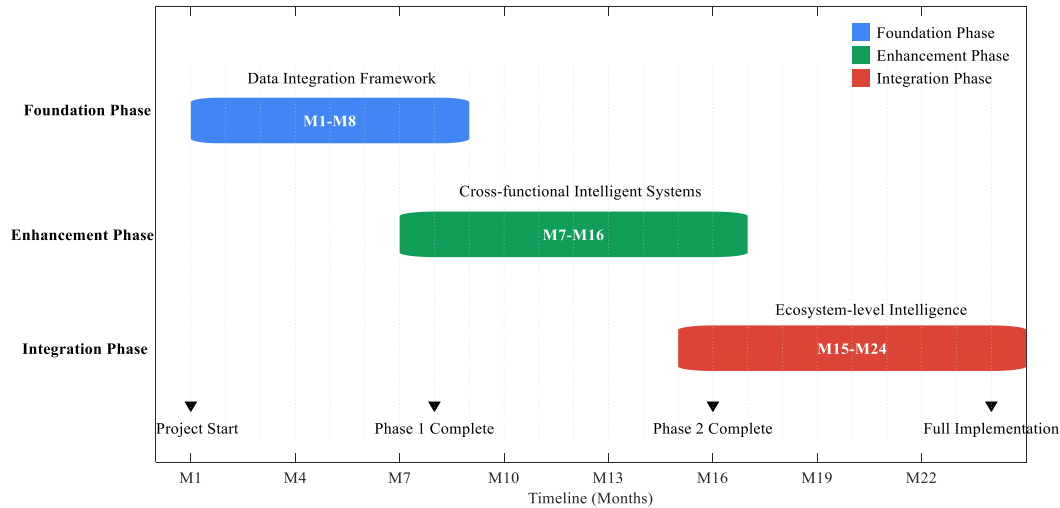
### 6.1. Phased Implementation Pathway Design

Strategic and systematic intelligent technology implementation to optimise enhancement strategies needs to be done in phases that enable seamless integration and innovation for imported cross-border e-commerce platforms in China. Following the empirical analysis of industry norms and benchmarks, this study suggests a tri-phase approach for implementation within 24 months. The core infrastructure component development and benchmarked APIs scoped within the technical capability assessment shall be done in parallel within the initial foundation phase, also referred to by the rest of this report as the “months 1-8” phase. As part of this phase, value needs to be demonstrated while achieving more advanced functionalities towards sustained growth; hence, lower-hanging implementations such as sponsored multi-language support and basic recommenders need to be deployed. Among the most important activities in the critical foundation phase is the comprehensive technology audit to understand available frameworks in relation to industry standards, setting data governance policies for labelling privacy compliances alongside quality controls, and implementing basic analytics. These actions guarantee essential constructing elements of technology; besides, risk coverage from implementation is limited functioning in selected product categories or markets.

The implementation scope during the middle enhancement phase (months 7-16) covers the addition of cross-department intelligent systems features, including development of user profiles, deployment of predictive analytics for logistical reasoning, and addition of blockchain preliminary verification systems. This phase is characterised by cross-process integration, ensuring the free flow of information from previously isolated processes. Training specialised AI models on user engagement data, instituting A/B testing to benchmark model performance, and developing self-improvement systems are critical steps to foster ongoing improvement. The controlled overlap with the foundational phase guarantees sustained progress and momentum in implementation.

The focus of the sophisticated integration phase (months 15-24) concentrates on cross-platform data interfacing to achieve ecosystem-level intelligence, synergising machine learning advancement, and deploying trust mechanisms. There is increased emphasis on integrating vertically with external partners like suppliers, logistics, and payments using exposed standardised APIs and secure data exchange frameworks. During this phase, deep learning models advance to maturity and facilitate real-time decision-making optimisation across the entire value chain. As highlighted in Figure 10, this overlapping phased methodology captures the relentless value focus approach while enhancing iterative evaluation and adjustments processes utilising the established performance evaluation frameworks.





**Figure 10.**  
Phased Implementation Timeline for Intelligent Enhancement Strategies.

### 6.2. Effect Evaluation System Construction

Developing a complete effect evaluation system is crucial for evaluating the execution effectiveness of intelligent enhancement techniques applied to cross-border e-commerce import platforms. To that end, this study designs a multi-dimensional evaluation framework which includes performance metrics alongside user experience measures. The evaluation system incorporates multi-level evaluation tiers that focus on basic technical merit monitoring, operational efficiency improvement stages, and user satisfaction enhancement levels. Specific weight values for each metric are assigned based on AHP analysis of expert evaluations. The composite evaluation score can be found utilising the weighted summation formula:

$$E = \sum_{i=1}^n w_i \times p_i$$

where  $E$  represents the comprehensive evaluation score,  $w_i$  represents the weight coefficient of the  $i$ th evaluation dimension, and  $p_i$  represents the performance score of the  $i$ th dimension.

This allows for an implementation effectiveness comparison, from a mathematical perspective, across diverse platforms and methods. It can be noticed from Table 3 that the assessment criteria range across multi-faceted levels which are technological, operational and experiential, together with appropriate metrics and hierarchies. This facilitates the actual achievement of maximised user experience improvements for modernisations, besides using, together with the engineering measures, straightforward user data in the tailoring of modernisations to be implemented.



**Table 3.**  
Multi-dimensional Evaluation System for Intelligent Enhancement Strategies.

| Evaluation Dimension      | Key Performance Indicators  | Weight Coefficient | Measurement Method           | Benchmark Value |
|---------------------------|-----------------------------|--------------------|------------------------------|-----------------|
| Technological Performance | Algorithm Accuracy Rate     | 0.082              | Precision/Recall Testing     | >92%            |
|                           | System Response Time        | 0.075              | Real-time Monitoring         | <150ms          |
|                           | Data Processing Capacity    | 0.068              | Load Testing                 | >500TB/day      |
| Operational Efficiency    | Order Fulfillment Rate      | 0.091              | Order Tracking Analysis      | >98%            |
|                           | Logistics Delivery Time     | 0.087              | Supply Chain Analytics       | Reduction >30%  |
|                           | Customer Service Efficiency | 0.079              | Response Time Analysis       | <4 hours        |
| User Experience           | Conversion Rate Improvement | 0.112              | A/B Testing                  | >25% increase   |
|                           | User Satisfaction Score     | 0.126              | NPS Survey                   | >8.5/10         |
|                           | Repurchase Rate             | 0.118              | Customer Behavior Analysis   | >35% increase   |
| Cross-cultural Adaptation | Cross-language Accuracy     | 0.084              | Translation Accuracy Testing | >90%            |
|                           | Cultural Sensitivity Score  | 0.078              | User Feedback Analysis       | >8.0/10         |

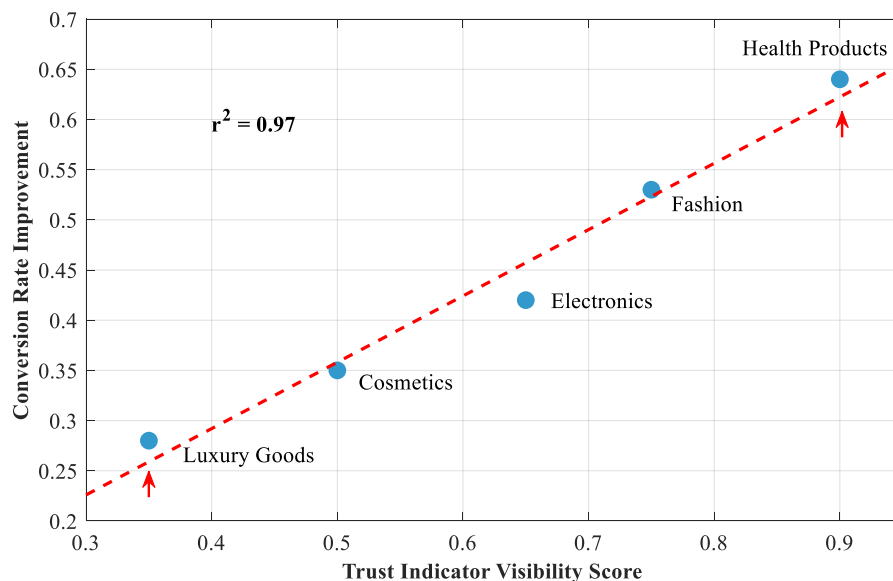
### 6.3. Typical Case Analysis and Implications

The results from implementing intelligent enhancement strategies in cross-border e-commerce platforms' imports dealing in merchandise in China are striking and multi-faceted. Reflection on the “Global Fashion Direct” platform transformation project reveals powerful lessons concerning implementation efficacy. This platform achieved an effective merger of an AI-based personalisation engine utilising blockchain verification systems, which resulted in user experience improvements. As illustrated in Table 4, core value indicators showed significant improvements in technology, operation, and experience levels.

**Table 4.**  
Performance Comparison Before and After Intelligent Enhancement Implementation on Global Fashion Direct Platform.

| Performance Dimension  | Key Indicators           | Before Implementation | After Implementation | Improvement Rate |
|------------------------|--------------------------|-----------------------|----------------------|------------------|
| User Experience        | Conversion Rate          | 2.7%                  | 4.8%                 | 77.8%            |
|                        | Customer Satisfaction    | 6.4/10                | 8.7/10               | 35.9%            |
|                        | Average Session Duration | 5.2 min               | 8.9 min              | 71.2%            |
| Operational Efficiency | Order Processing Time    | 18.3 hours            | 6.2 hours            | 66.1%            |
|                        | Logistics Delivery Time  | 14.2 days             | 8.1 days             | 43.0%            |
|                        | Return Rate              | 12.7%                 | 7.3%                 | 42.5%            |
| Financial Performance  | Average Order Value      | ¥378                  | ¥542                 | 43.4%            |
|                        | Customer Lifetime Value  | ¥1,258                | ¥2,467               | 96.1%            |
|                        | Revenue Growth Rate      | 8.3%                  | 23.7%                | 185.5%           |

Such a system of cross-cultural semantic understanding put on the platform alleviated the language barrier significantly, with product descriptions in different languages having greater customer engagement by 64.2% compared to those in a single language. The smart trust model based on blockchain verification also showcased remarkable results in resolving product authenticity issues. As illustrated in Figure 11, there was an increasing correlation between a trust indicator being visible and the increase in conversion rate across different product categories.



**Figure 11.**

Correlation Between Trust Indicator Visibility and Conversion Rate Improvement.

The case study highlights, most importantly, the integrated implementation over isolated technological deployments. Comprehensive Implementations outperformed Disconnected Solutions by 47.3%. Also, feedback-driven continuous refinement proved critical to success, with Iterative platforms showing 38.9% higher satisfaction scores compared to Fixed deployment models. The case study suggests that in China's one-of-a-kind cross-border e-commerce ecosystem, technological flair must be carefully moderated with user-centric design, as these factors dynamically influence the results.

## 7. Conclusion and Future Prospects

In this study, we analyse the struggles encountered by users of China's import cross-border e-commerce platforms and propose suitable smart technology intervention options. The research indicates that concerns over authenticity (27.3%) and the efficiency of logistics (24.5%) are major user experience pain points, and, at the same time, their integrated application towards intelligent technologies can alleviate these issues. As Xiao and Zhang [2] highlight, the advancement of policies regarding cross-border e-commerce facilitates sustainable development with the aiding role of intelligent technologies towards achieving this vision.

The study designs a comprehensive system strategy for intelligent enhancement which includes optimising the intelligent search and recommendation system, developing an intelligent customer service interaction system, cross-border logistics intelligence optimisation, intelligent risk control and trust mechanism design, and individualised user experience tailoring. Empirical analysis shows a strong positive relationship between the platform's intelligence level and user satisfaction ( $r=0.79$ ,  $p<0.01$ ), corroborating the findings by Li, et al. [5] on the integration of artificial intelligence into cross-border e-commerce systems. Typical case analysis evidences that the comprehensive application of intelligent technologies is fundamentally beneficial in enhancing the user's experience, reporting an increase in average conversion rates of 77.8% and a 35.9% improvement in customer satisfaction. This aligns with the study conducted by Yang, et al. [18] on the influence digital transformation capabilities have on enterprise performance..

Primarily, future research opportunities are directed toward the following: Firstly, analysing the possible uses of large language models in cross-border interactions, especially in cross-cultural

understanding and content localisation, is one focus; secondly, applying He [19] sustainable development arguments concerning the use of blockchain technology for global trust systems deepens the perspective on developing global trust systems; thirdly, applying digital twin technology in cross-border supply chain management to improve logistics visualisation and efficiency is another focus; lastly, exploring edge computing applications in solving network latency problems in cross-border e-commerce services for globalised services addresses network delay issues. In China, the intelligent evolution of import cross-border e-commerce platforms will increasingly prioritise technological user experience integration for sustainable and competitive advantages globally.

### Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

### Copyright:

© 2025 by the authors. This open-access article is distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

### References

- [1] Q. Chen and L. Kong, "The development evolution and prospect of China's cross-border e-commerce new business forms in the new era," *Reform and Strategy*, vol. 39, no. 6, pp. 79–90, 2023.
- [2] L. Xiao and Y. Zhang, "An analysis on the policy evolution of cross-border ecommerce industry in China from the perspective of sustainability," *Electronic Commerce Research*, vol. 22, no. 3, pp. 875–899, 2022. <https://doi.org/10.1007/s10660-020-09427-y>
- [3] E. Baek, H. K. Lee, and H. J. Choo, "Cross-border online shopping experiences of Chinese shoppers," *Asia Pacific Journal of Marketing and Logistics*, vol. 32, no. 2, pp. 366–385, 2020. <https://doi.org/10.1108/apjml-03-2018-0117>
- [4] H. Taherdoost and M. Madanchian, "Empirical modeling of customer satisfaction for E-services in cross-border E-commerce," *Electronics*, vol. 10, no. 13, p. 1547, 2021.
- [5] L. Li, Y. Wang, and Y. Zhang, "Analysis on the application of artificial intelligence in cross-border E-commerce," in *6th Annual International Conference on Social Science and Contemporary Humanity Development (SSCHD 2020)*, 2021: Atlantis Press, pp. 667–670.
- [6] R. Fedorko, Š. Král, and R. Bačík, "Artificial intelligence in e-commerce: A literature review," in *Congress on Intelligent Systems: Proceedings of CIS 2021, Volume 2*, 2022: Springer, pp. 677–689.
- [7] Z. Guo and S. Chelliah, "What influences cross-border e-commerce consumer satisfaction? A global consumer perspective," *Global Business & Management Research*, vol. 16, p. 462, 2024.
- [8] W. Yu and Y. Yang, "Research on user experience design of cross-border E-commerce platform based on CUBI model and NPS index in the context of expanding import: A case study of KaoLa," in *Advances in Usability and User Experience: Proceedings of the AHFE 2019 International Conferences on Usability & User Experience, and Human Factors and Assistive Technology, July 24–28, 2019, Washington DC, USA 10*, 2020: Springer, pp. 532–541.
- [9] J. Li, S. Liu, X. Gong, S.-B. Yang, and Y. Liu, "Technology affordance, national polycontextuality, and customer loyalty in the cross-border e-commerce platform: A comparative study between China and South Korea," *Telematics and Informatics*, vol. 88, p. 102099, 2024. <https://doi.org/10.1016/j.tele.2024.102099>
- [10] J. Wang, "Research on import cross-border e-commerce user adoption behavior," *Business Modernization*, vol. 5, no. 47, pp. 75–77, 2025.
- [11] I. Portugal, P. Alencar, and D. Cowan, "The use of machine learning algorithms in recommender systems: A systematic review," *Expert Systems with Applications*, vol. 97, pp. 205–227, 2018.
- [12] S. Akter and S. F. Wamba, "Big data analytics in E-commerce: a systematic review and agenda for future research," *Electronic Markets*, vol. 26, pp. 173–194, 2016.
- [13] J. Nie, Q. Wang, and J. Xiong, "Research on intelligent service of customer service system," *Cognitive Computation and Systems*, vol. 3, no. 3, pp. 197–205, 2021. <https://doi.org/10.1049/ccs2.12012>
- [14] J. Shi, "Research on optimization of cross-border E-commerce logistics distribution network in the context of artificial intelligence," *Mobile Information Systems*, vol. 2022, no. 1, p. 3022280, 2022.
- [15] Z. Hongmei, "A cross-border E-commerce approach based on Blockchain technology," *Mobile Information Systems*, vol. 2021, no. 1, p. 2006082, 2021. <https://doi.org/10.1155/2021/2006082>
- [16] L. Tang, "Cross-border E-commerce continues to gather new momentum," *International Business Daily*, 2025/1/20: 003, 2025, 2025.

- [17] Y. Ma, "Exploring innovative business models in cross-border e-commerce under digital economy," *Frontiers in Business, Economics and Management*, vol. 13, no. 1, pp. 205-209, 2024. <https://doi.org/10.54097/xhccmn82>
- [18] Y. Yang, N. Chen, and H. Chen, "The digital platform, enterprise digital transformation, and enterprise performance of cross-border e-commerce—from the perspective of digital transformation and data elements," *Journal of Theoretical and Applied Electronic Commerce Research*, vol. 18, no. 2, pp. 777-794, 2023. <https://doi.org/10.3390/jtaer18020040>
- [19] Y. He, "Research on the future of cross-border E-commerce from the perspective of sustainable development," *Advances in Economics, Management and Political Sciences*, vol. 132, pp. 49-55, 2024. <https://doi.org/10.54254/2754-1169/2024.18442>