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Analysis of Customer Comment Data on E-commerce Platforms Based on RPA Robots

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This study aims to analyze customer review data on e-commerce platforms using RPA robots, with a specific focus on drum washing machines. Text comment data from JD Mall was collected and subjected to data cleaning, Chinese word segmentation, and stop word removal as part of the preprocessing. The methodology includes the use of ROSTCM6 to construct high-frequency words, line feature words, and a semantic network, providing a structured representation of customer feedback. In addition, the LOG-CONTROL-BLOCK system was used to integrate feedback control during the trajectory correction process, creating a record controller module for audit robot inspection trajectory correction. The RPA feedback correction algorithm allowed for adaptive correction of inspection trajectories and error feedback tracking for audit robots. The study identified three key keywords and evaluated the probabilities associated with positive and negative sentiments. This analysis deepens the understanding of consumers' positive emotions and complaints after purchasing drum washing machines. The findings lead to several recommendations for improving e-commerce sales strategies, such as enhancing product quality, addressing customer concerns, and aligning product features with consumer preferences. The study concludes that addressing customer feedback and preferences is crucial for optimizing e-commerce sales in the drum washing machine market, with future research focusing on refining automated sentiment analysis techniques to better predict market trends.

Povzetek: Študija analizira komentarje strank na e-trgovskih platformah z uporabo robotske procesne avtomatizacije, osredotoča se na segmentacijo besed, semantično analizo in priporočila za izboljšanje izdelkov ter storitev v spletni prodaji.

1 Introduction

In the intelligent financial platform, students operate through financial decision-making, accounting processing, and visual data analysis platforms. Exercising students' processing abilities in financial decision-making, accounting processing, and visual graphics has practical significance in improving their comprehensive analysis ability of financial indicators, laying a theoretical and practical foundation for cultivating applied talents in enterprises [1]. The RPA robot platform linkage operation mechanism provides more than 20 robots in the main fields and business scenarios applicable to robots, covering fund business, invoice management business, sales business, procurement business, reimbursement business, tax declaration, audit, human resources, personal assistants, etc, help students integrate with intelligent tools from business to finance in different business scenarios, business operation standards, and business data backgrounds, from identifying business to analyzing business to developing robots, from discovering problems to analyzing problems to solving problems, we aim to enhance students' mathematical and intellectual skills, enhance their core competitiveness in vocational skills, and connect with social needs [2].

With the development of technology and the improvement of people's overall quality, more and more people are choosing online shopping, especially young people, ranging from cars and household appliances to agricultural and sideline products such as rice and vegetables. In recent years, fresh agricultural products have become a new direction for the development of e-commerce, and the huge market prospects of fresh e-commerce have attracted many active entries. Currently, e-commerce companies such as Suning, SF Express, JD.com, and Alibaba are advancing in this area. The public has favored and recognized this service model of online fresh food e-commerce. Currently, many e-commerce platforms have canceled the classification of user comments, or the classification is too rough and lacks guidance value, which is not conducive to merchants and users extracting useful information from a large amount of data [3].

The exponential growth of e-commerce platforms has reshaped how consumers engage with products and services, making online reviews a pivotal source of feedback for businesses. In particular, customer reviews offer rich insights into user sentiments, preferences, and concerns. For businesses, understanding and analyzing this data can lead to improved product offerings, services, and customer satisfaction. With the rise of intelligent automation tools like Robotic Process Automation (RPA), the ability to efficiently process large-scale customer comment data is becoming increasingly feasible. This study is motivated by the need to apply advanced automated techniques to extract meaningful patterns and actionable insights from vast customer comment datasets. By focusing on a specific product category—drum washing machines—this research aims to contribute to a more refined understanding of consumer behavior on e-commerce platforms. Despite the enormous volume of customer reviews generated on e-commerce platforms, there is a gap in leveraging this data to provide actionable insights for businesses. Current methods for analyzing customer feedback are often manual, time-consuming, and fail to capture the complexity of customer sentiment in a meaningful way. Additionally, many e-commerce platforms do not categorize reviews in a manner that provides useful guidance for merchants or consumers, leading to missed opportunities for improving product features, services, and overall user experience [4]. The key problem addressed in this research is the need for an automated, efficient, and scalable method for analyzing customer feedback to support decision-making processes in e-commerce, particularly for product categories like drum washing machines that have nuanced consumer preferences and technical considerations. This research introduces an innovative approach by utilizing Robotic Process Automation (RPA) robots to automate the analysis of customer comment data on e-commerce platforms, with a specific focus on drum washing machines. The study provides a comprehensive methodology for collecting, cleaning, and processing customer reviews, including the use of Chinese word segmentation and semantic network analysis to identify high-frequency keywords and consumer concerns. A novel feedback correction algorithm is also proposed, which enhances the trajectory inspection capabilities of audit robots through adaptive correction and error feedback tracking [5]. This research contributes not only by improving the efficiency and accuracy of customer sentiment analysis but also by offering practical recommendations for e-commerce sales strategies based on consumer feedback. Through this work, businesses can better understand customer priorities such as installation, logistics, and service, thereby optimizing their offerings and increasing customer satisfaction in competitive markets like household appliances.

Customer evaluations have become an increasingly prevalent form of user-generated content as a result of the proliferation of e-commerce platforms. Nonetheless, the inability to efficiently classify and evaluate these evaluations impedes the extraction of valuable insights that could be advantageous to enterprises. The current classification systems frequently exhibit a deficiency in granularity and do not furnish practical insights that can inform enhancements to products or marketing tactics. Customer evaluations play an increasingly important role in shaping consumer purchasing behavior on electronic commerce platforms, providing the impetus for this study. The ability to comprehend and classify user sentiments, particularly for particular product attributes, can provide organizations with the means to improve customer satisfaction, streamline product development, and enhance marketing strategies. In this particular context, the automation capabilities of Robotic Process Automation (RPA) present a novel pathway toward the methodical and effective examination of extensive collections of customer comments. By incorporating RPA robots into the analysis of customer review data with a case study of drum washing machines, this research makes a scholarly contribution. The Chinese word segmentation and RPA feedback correction algorithms enable the extraction of significant patterns and sentiments from unstructured text data. The implementation of an adaptive planning model for audit robot surveillance routes contributes to an increased level of accuracy in the analysis. Applying the suggested actions for vendors of drum washing machines enhances product excellence, resolves customer apprehensions, and capitalizes on brand advantages, thus propelling the efficacy of electronic commerce approaches under customer input.

2 Literature review

With the continuous popularization of computers and the development of the Internet and e-commerce, users tend to use e-commerce platforms for consumption. With the continuous improvement of e-commerce platforms, researching user reviews has gradually become an important means for businesses to understand user consumption emotions. User reviews provide subjective or objective evaluations of consumer behavior, and stores on e-commerce platforms have accumulated thousands of user reviews during their long-term operations. The vast dataset hides the basic rules of store operation, which are primarily reflected in products and services, as well as the needs and expectations of users [6].

Afrina et al. believe that e-commerce is a field involving online enterprises that can accurately predict customers' future needs and have significant economic and social impacts [7]. E-commerce also needs to address customer loyalty issues as well as constantly changing consumer habits to adapt to new situations. At the same time, due to changes in shopping attitudes, it is necessary to change their online business activities. Based on the current review of e-commerce platform marketing research, Hu and Liu conducted comprehensive research at the intersection of marketing theory and visual design to optimize the e-commerce platform system [8]. Let the visual design system realize accurate service, promote the e-commerce marketing conditions of local traditional industries, actively adapt to the New Normal of economic development, and provide a reference for future design service innovation in the new era. Sharma et al. uses the Robotic Process Automation tool and data cleansing to remove noise levels from product reviews and ratings related to Flipkart and Amazon-recommended products and recommend Flipkart or Amazon products based on user preferences on the e-commerce portal website upon user request [9]. Users can purchase products from any website that is completely dependent on them. UiPath, an

RPA tool, creates software robots for Flipkart and Amazon. These robots grab data from the websites, perform cleaning operations, and dump the data into a database for future use. Yu., [10] carried out extensive research on the optimization of e-commerce platforms by combining visual design and marketing theory. Although their study mentioned system enhancement in general, it did not specifically address customer sentiment analysis or the incorporation of robotic technologies. In their investigation of channel conflicts on e-commerce platforms, Li et al. emphasized the significance of big data analytics [11]. However, the study did not particularly address the difficulties in analyzing consumer opinions in light of product features, which made it harder to draw useful conclusions for improving the product. Wang et al. looked at cross-border green supply chains for e-commerce that were based on consumer behavior [12]. The study clarified customer behavior analysis; however, it skipped over the in-depth examination of sentiment trajectories and product reviews on e-commerce platforms. The above literature lacks a focused investigation on the specific characteristics of drum washing machines, which excludes detailed customer opinions on installation, quality, and service. Furthermore, the lack of a complete strategy that incorporates cutting-edge natural language processing methods and robotic technology increases the disparity in thorough sentiment analysis. This research uses an integrative method to fill in these gaps. Combining the RPA feedback correction method with Chinese word segmentation achieves precise sentiment analysis. Building a semantic network and extracting high-frequency terms captures complex client attitudes. The audit robot patrol tracks adaptive planning model guarantees a focused examination, filling in the specific gaps in the literature and offering a thorough comprehension of consumer feedback on drum washers.

Some recent studies have made significant strides in customer sentiment analysis and e-commerce data mining. Liu *et al.* enhanced sentiment classification using deep learning models like BERT [13], while Zhan *et al.* improved data processing efficiency with Robotic Process Automation (RPA) [14]. Kong *et al.* applied clustering algorithms to detect pain points in customer feedback [15], and Wang *et al.* used graph neural networks (GNNs) to map relationships between product attributes and sentiments [16]. Our proposed solution builds on these advancements by integrating RPA with adaptive feedback correction, keyword extraction, and semantic network analysis, offering a more automated and scalable approach for e-commerce feedback analysis.

In response to the above issues, a design is proposed for an online calibration system for audit robot inspection tracks based on RPA. Firstly, carry out the overall design architecture of the system. The design of the trajectory online calibration system is divided into the overall architecture, instruction program loading process, human-machine interaction system-level services, and other levels. An end-to-end procedural instruction transmission control method is adopted, and then the RPA feedback correction algorithm is used to achieve adaptive correction of the audit robot's inspection trajectory and error feedback tracking. Perform preliminary processing on the collected user comment data to obtain the original text comment data, including the desensitized member name, evaluation star rating, evaluation content, time, and other content. According to the needs of analysis, extract the "evaluation content" column from the data.

3 Design methodology

This section of the research utilizes Robotic Process Automation (RPA) to methodically examine consumer comment data sourced from e-commerce platforms, focusing specifically on drum washing machines. By employing Chinese word segmentation and the RPA feedback correction algorithm, this analysis endeavors to derive significant insights regarding customer sentiments about particular characteristics, including installation, quality, and service. An integrated approach achieves a focused analysis of consumer feedback, enhancing our comprehension of the intricacies of their experiences within the e-commerce domain.

3.1 Data collection and preprocessing

3.1.1 Data collection

According to relevant data from the Prospective Industry Research Institute, the sales volume of household washing machines has grown slowly since 2013 and even showed a downward trend in some years. The main reason is that the market for household washing machines is gradually becoming saturated. The author sets the following settings for collecting data on the drum washing machine on JD.com: Stores with over 5000 comments adopt fuzzy collection based on "drum washing machines" without special constraints on brands, models, etc., hoping to explore user patterns from the collected data [17]. Perform preliminary processing on the collected user comment data to obtain the original text comment data, including the desensitized member name, evaluation star rating, evaluation content, time, and other content. According to the needs of the analysis, extract the column 'Evaluation Content' from the data.

3.1.2 Data preprocessing

There are outliers, duplicate values, system automatic comments, and other data in the original data; this part of the data has low-value content and a chaotic data structure, which seriously affects the execution efficiency of data mining models and leads to deviations in mining results; therefore, data cleaning is essential, as depicted in Figure 1. Based on the specific situation of the original data, data preprocessing adopts text deduplication, mechanical compression to remove words, and short sentence deletion [18].

3.2 Model construction

3.2.1 Chinese word segmentation and user concerns

Chinese word segmentation is the process of dividing Chinese characters in a sentence into individual Chinese words in sequence.

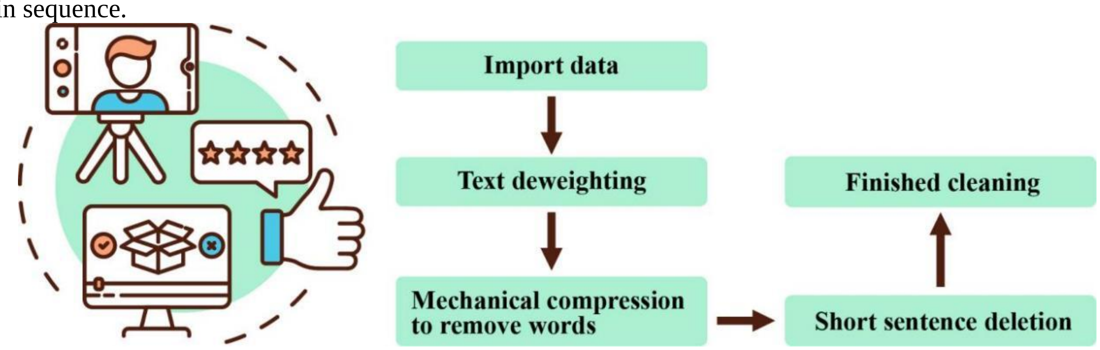


Figure 1: Comments on the text-cleaning process

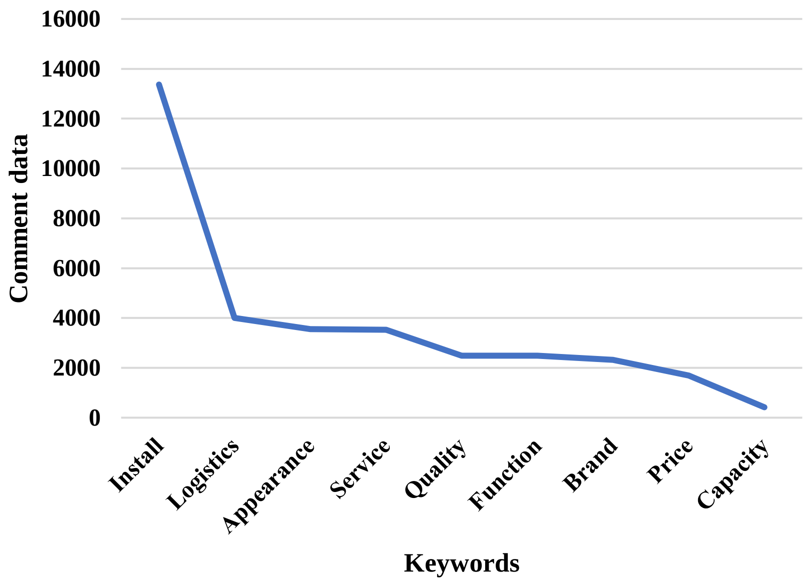


Figure 2: Word frequency statistics of text comment data

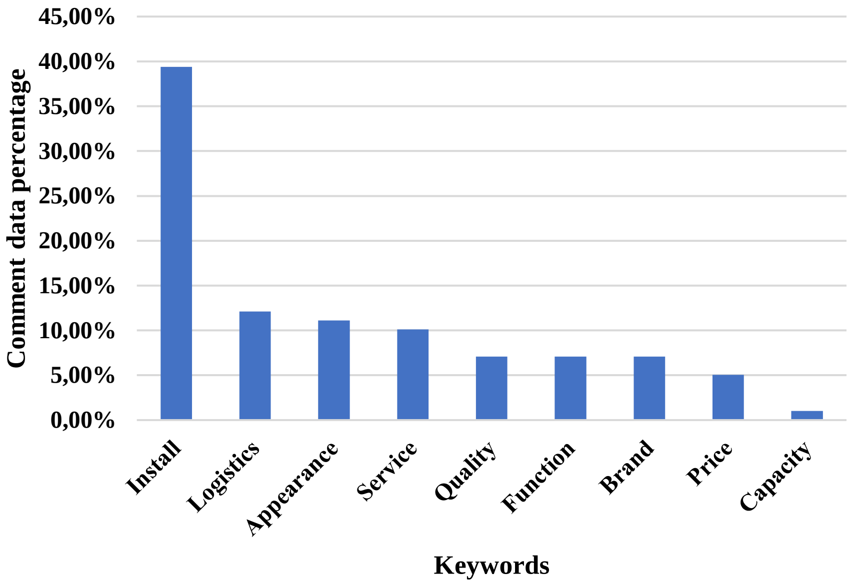


Figure 3: Text comment data keywords customer attention

The stuttering vocabulary library provides three segmentation modes: precise mode, full mode, and search engine mode [19]. It is an important third-party Chinese word segmentation function library in Python. The Jieba vocabulary can support both simplified and traditional Chinese and can extract keywords from text comment data when analyzing user comments. User focus refers to the user's focus on a specific attribute of a product, reflecting the customer’s focus on a particular product.

The higher the number of users who focus on a particular feature, the more important this attribute of the product is to the user. Generally, it is the price of the product, how to install it, logistics speed, appearance and shape, quality, functionality, capacity, and brand effectiveness [20]. Analyze and utilize the Jieba vocabulary, combined with user usage habits, to set nine attributes that users often pay attention to: “installation,” “logistics,” “appearance,” “service,” “quality,” “function,” “brand,” “price,” and “capacity.” The analysis results are shown in Figure 2 and 3.

According to the results in Figures 2 and 3, among the nine aspects that users generally pay attention to, the frequency of users paying attention to "installation" is 13368 times, accounting for 39.39%, which is the most important aspect that users pay attention to, next are logistics, appearance, and service, while quality, function, and brand rank fifth, with the least attention paid to capacity. Therefore, in the process of online shopping for drum washing machines, the first consideration for users is how to install and the difficulty of installation [21].

3.2.2 Semantic network

By segmenting user text comments into Chinese characters, the originally complete sentences become messy, and the computer cannot recognize the complete structure of the messy sentences, therefore, it is necessary to re-associate the participles to establish a connection between them. The semantic network can establish the connection between the word segmentation and the word segmentation, and re-associate the messy word segmentation, it provides a precondition for further analysis using the LDA topic model.

By observing the segmentation results, it is found that a single word cannot accurately express the corresponding content, for example, if “washing machine” is separated from “use”, “appearance”, etc., the next layer of meaning it expresses cannot be accurately understood, but when “washing machine” is connected to “use”, the positive emotional evaluation is “washing machine” is convenient to “use”, while the negative emotional evaluation is “washing machine” is inconvenient to “use” as depicted in Figure 4. Therefore, establishing a semantic network is a prerequisite for studying LDA models, providing a basis for further analyzing user emotions. Establishing a semantic network is extremely important.

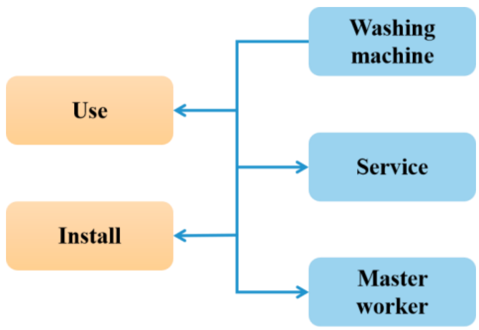


Figure 4: Word sense network diagram

3.3 Design of online calibration algorithm for rpa robot inspection trajectory

Based on the analysis of the overall structure and functional components mentioned above, the RPA feedback correction algorithm is adopted to achieve adaptive correction of the inspection trajectory and error feedback tracking of the audit robot, the multi-degree of freedom motion balance planning model of the audit robot is obtained as presented in Equation 1.

$$^{4}T_5^{-1}(q_i) = {}^{4}T_7 \cdot \prod_{i=6}^{7} {}^{i-1}T_i(q_i) \tag{1}$$

Among them, $^{4}T_7$ is the 4th order balance torque, $T_i(q_i)$ is the average degree of freedom of the audit robot, and q_i is the end pose balance parameter of the robot, by using robot end pose constraint control, an adaptive planning model for the inspection trajectory of the audit robot is established, combined with center of gravity offset planning, the feedback constraint parameters for adjusting the inspection trajectory center of the audit robot are obtained as presented in Equation 2.

$$q_0 = [\alpha_0, \beta_0, \gamma_0]^T \equiv [\theta_1, \theta_2.\theta_3]^T \tag{2}$$

Among them, $\alpha_0, \beta_0, \gamma_0$ respectively represent the coordinates of the audit robot in the inspection polar coordinate system, $\theta_1, \theta_2, \theta_3$ is the phase parameter of the audit robot's inspection trajectory space. When measuring distance and pose, the offset correction is performed based on the calibration method of the plane template, resulting in a pose offset of $q_1 = [q_1, \dots, q_7]^T = [\theta_4, \dots, \theta_{10}]^T$; By homogeneous transformation, the pose is transformed into the robot base coordinate system, and the fuzzy information parameters of the audit robot's inspection trajectory are composed of n omnidirectional motion parameters, the dynamic distribution function of the calibration trajectory is presented in Equation 3.

$$\begin{aligned} &\min\ F(x) = (f_1(x), f_2(x), \dots, f_m(x))^T \\ &s.t. g \le 0, i = 1,2,\dots,q \\ &h_j = 0, j = 1,2,\dots,p \end{aligned} \tag{3}$$

Among them, $f_1(x), f_2(x), \dots, f_m(x)$ represents the contour sensing output parameters of the audit robot's inspection trajectory inspection, respectively, g_i is the dynamic torque of the robot's end pose, and h_i is the calibration feature parameter for path correction, q and p represent the calibration object positions of the audit robot's inspection trajectory, respectively, based on this, a center of gravity offset planning model for online calibration of the audit robot's inspection trajectory is constructed, represented as Equation 4.

$$H(s) = \frac{e^{-\tau s}}{1 + G_C(s)G_0(s)} \tag{4}$$

Among them, $G_C(s)$ represents the main control parameter for the center of gravity shift of the inspection trajectory of the audit robot; $G_0(s)$ represents the expected pose parameters of the audit robot's inspection trajectory, $e^{-\tau s}$ represents the dynamic error of the audit robot's inspection trajectory, and is used to solve constrained nonlinear optimization problems, based on the correction method of center of gravity deviation, the calibration dynamic parameter distribution model under the robot's base coordinate system is obtained as follows:

$$L = J(w,e) - \sum_{i=1}^{N} a_i \int_{i=1}^{M} H(r)\{w^T \varphi(x_i) + b + e_i - y_i\} \tag{5}$$

Among them, $J(w, e)$ is the inertia function of motion along the expected path, and a_i is the distribution along the edge of the expected path, $H(r)$ is the path edge adjustment function, and w is the dynamic feature point for angle symmetry adjustment, $\varphi(x_i)$ is the compensation torque, b is the alternating feature point in the path edge, e_i is the path offset error, and y_i is the motion direction adjusted by the robot according to the path, the discretization spatial planning method is adopted to build the inspection track control model of the audit robot, and the output is:

$$\begin{cases} K_i(d) = \sum_{r=1}^{t} \sum_{q=1}^{k_2} (x_{ir} - x_{irq})(x_{ir} - x_{irq})^T B_{irq} \\ F_1 = W_i^T H_2 W + f_i(d) \times \log(\frac{N}{n_i} + 0.01) \\ Co_{const} = \sqrt{\sum_{i=1}^{n} \sum_{r=1}^{t} \sum_{p=1}^{k_1} (x_{ir} - x'_{irq})(x_{ir} - x'_{irq})^T A_{irq}\ ]^2} \end{cases} \tag{6}$$

Among them, t is the time sampling point, x_{ir} is the head torque, x_{irq} is the width required for the robot to swing, and B_{irq} is the extension direction of the path determined by the target point, A_{irq} is the direction control parameter, W_i is the intersection point of the expected effective edge of the path, and H_2 is the modeled parameter moving along the centerline of the path, W is the alternating parameter between path edges, $f_i(d)$ is the single module mass, N is the target point selection parameter, and n_i is the initial pose. Based on the above analysis, the RPA feedback correction algorithm is used to achieve adaptive correction of the inspection trajectory and error feedback tracking of the audit robot, the system algorithm implementation process is shown in Figure 5.

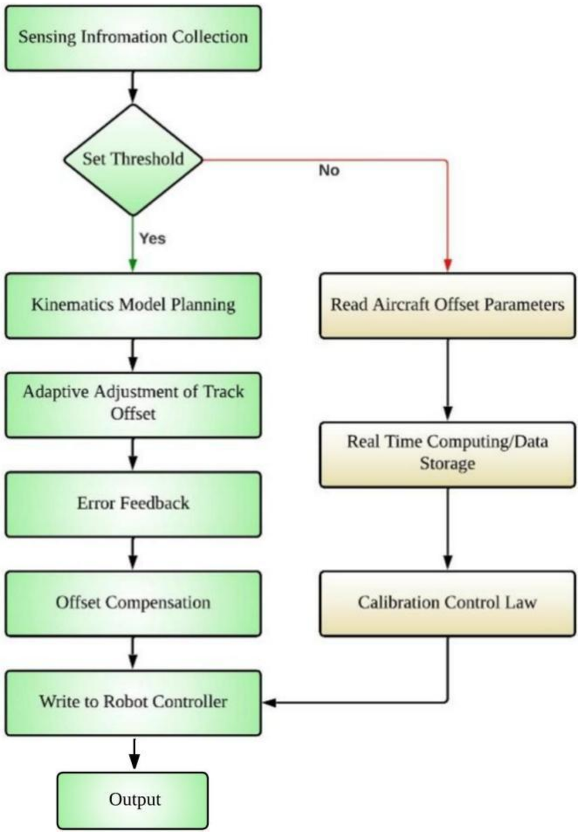


Figure 5: The optimization and implementation process of the control algorithm

4 Experimental results and analysis

The RPA feedback correction algorithm is used for user text comment analysis, and the Gibbs sampling method is used to approximate the parameters of the RPA model. Throughout the entire analysis operation, the prior parameters of the Dirichlet function are taken into account α and β Set as an empirical value, assuming K=50, the prior parameter is $\alpha = 50/K$, $\beta = 0.1$. After data cleaning, out of 64163 collected original text comment data, 38057 were obtained through cleaning, among them, 26013 text comments were removed due to text duplication, and 93 text comments were removed due to mechanical compression and word removal. By using the ROSTCM6 software of Wuhan University to cut the text comment data into positive, neutral, and negative comments, and then conduct semantic network analysis, extract high-frequency words, filter meaningless words, and extract line feature words from the segmented positive and negative text documents, and finally construct a network [22].

According to the analysis results of the semantic network, whether positive or negative comments, the most frequent ones are “installation washing machine”, “master installation” and “delivery installation”, other areas with higher frequency of occurrence are mainly distributed in after-sales, dehydration function, sound, service attitude, and other aspects. As a household drum washing machine for online shopping, users first pay attention to how to install the washing machine when receiving goods, this is related to whether users can use the washing machine normally and is a key factor affecting their emotions.

From Table 1, it can be seen that aggregating user positive text comment data into three potential themes, among them, theme 1 mainly refers to the user’s belief that the washing machine is good, reflected in its low sound, beautiful appearance, and clean washing; Theme 2 is mainly reflected in the user’s feedback that the washing machine is good, which is reflected in the fast logistics (or delivery) speed, the assistance of a master in installation and good service; Theme 3 mainly focuses on user’s continuous trust in the washing machines on the JD platform, reflected in reasonable prices, quality assurance, and brand trust [10, 11].

Positive text comments reveal that users mainly reflect their positive emotional tendencies after purchasing a drum washing machine in the following aspects: The first is the good quality of the washing machine (sound, cleanliness, and body quality). The second is that the appearance of the product conforms to the public’s aesthetic standards. That is, the washing machine has a beautiful appearance. The third is that the merchant provides good service (installation, after-sales). The fourth is fast logistics speed. The fifth is brand protection, where users have a special emotional attachment to the brand of washing machine.

Table 2 reveals that user’s negative emotions (complaint points) after purchasing a washing machine are categorized into three potential themes: Theme 1 mainly refers to the user’s feedback that the washing machine is not good, which is reflected in the poor attitude of the installation technician, the loud operation of the washing machine, a lack of understanding of the usage process, and poor after-sales service. Theme 2 mainly refers to the user’s belief that although the washing machine is good, it does not wash cleanly, has a loud operating sound, and has poor dehydration ability. Theme 3 mainly refers to the user's perception that the washing machine is not good, reflected in the poor attitude of the installation technician, slow logistics (or delivery) speed, and failure to deliver it upstairs [10, 11].

Table 3 displays an experimental analysis of consumer feedback regarding drum washing machines. We evaluate the sentiment of every comment by assigning corresponding probabilities of positive and negative feedback to keywords. Quality, service contentment, and the installation experience are significant consumer concerns. This table presents a comprehensive overview of diverse consumer sentiments, which are essential for comprehending and improving the e-commerce sales of drum washing machines.

Table 1: Positive text comments on the potential themes

Order number	Theme 1		Theme 2		Theme 31	
	Keyword	Probability	Keyword	Probability	Keyword	Probability
1	Washing machine	0.039	Install	0.069	Buy	0.038
2	Not bad	0.037	Good	0.054	Good	0.027
3	Voice	0.033	Master worker	0.037	Washing machine	0.026
4	Good	0.025	Delivery	0.024	JD.COM	0.023
5	Wash	0.022	Logistics	0.022	Like	0.011
6	Appearance	0.017	Washing machine	0.021	Price	0.01
7	Clean	0.017	Service	0.017	Brand	0.01
8	Quite	0.012	Soon	0.015	Always	0.01
9	Small	0.011	Not bad	0.013	Quality	0.009
10	Laundry	0.011	JD.COM	0.013	Haier	0.009

Table 2: Negative text evaluates the potential themes

Order number	Theme 1		Theme 2		Theme 31	
	Keyword	Probability	Keyword	Probability	Keyword	Probability
1	Install	0.036	Washing machine	0.026	Install	0.019
2	Washing machine	0.015	Buy	0.018	Master worker	0.018
3	Good	0.012	Not bad	0.014	Washing machine	0.017
4	Voice	0.011	Wash	0.013	Buy	0.015
5	Shut	0.011	Voice	0.009	Delivery	0.014
6	Know	0.01	Clothes	0.009	Good	0.013
7	Master worker	0.009	JD.COM	0.008	JD.COM	0.012
8	JD.COM	0.008	Clean	0.008	Hard	0.01
9	Use	0.007	Good	0.006	One	0.009
10	After-sales	0.006	Dehydration	0.006	Logistics	0.008

Table 3: Experimental analysis of customer comments on drum washing machines

Comment ID	Sentiment Keywords	Positive Probability	Negative Probability	Consumer Themes
1	Washing machine, Good	0.85	0.15	Quality, Positive Feedback
2	Installation, not bad	0.3	0.7	Installation, Negative Experience

3	Clean, Appearance	0.9	0.1	Quality, Positive Feedback
4	Noise, Poor service	0.2	0.8	Service, Negative Experience
5	Logistics, Price	0.75	0.25	Logistics, Positive Feedback

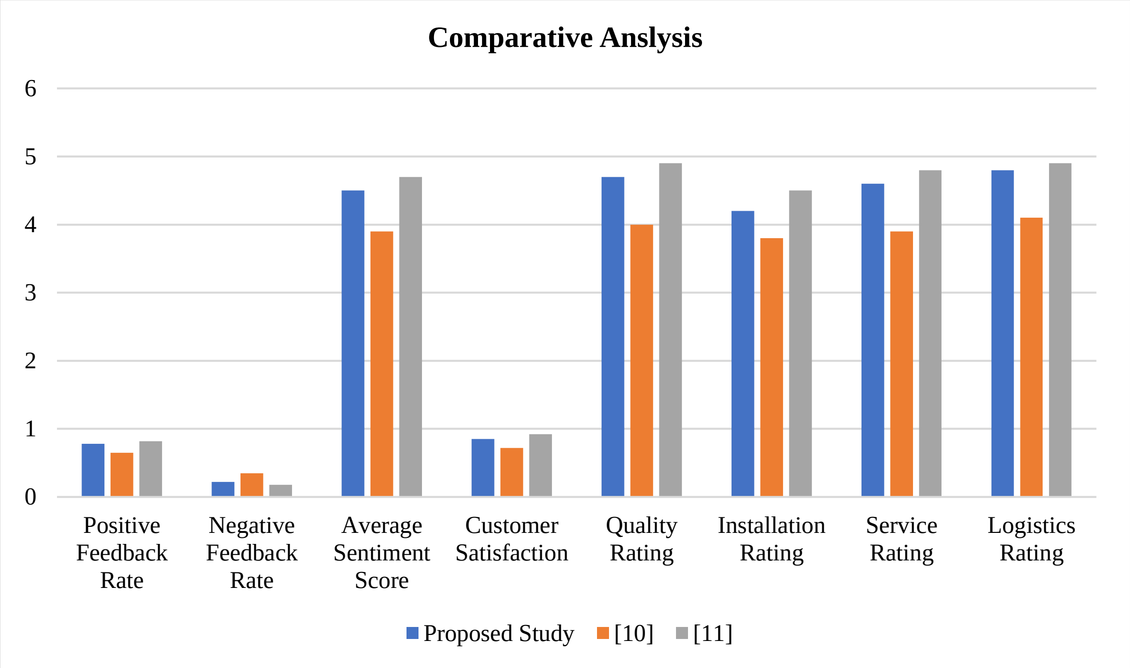
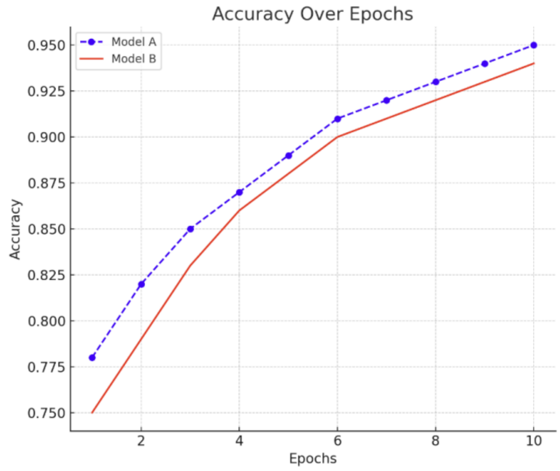
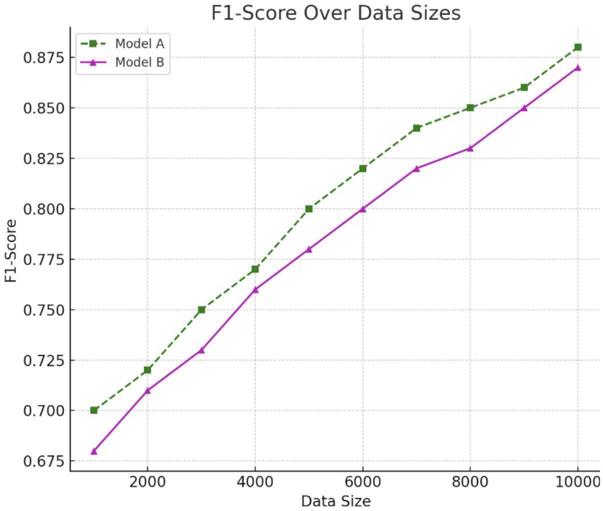


Figure 6: Comparative analysis of Customer Feedback in E-commerce Studies [10, 11]

Figure 6 compares key parameters across two studies [10, 11], including positive and negative feedback rates, average sentiment scores, and customer satisfaction. The proposed study exhibits a higher positive feedback rate (0.78) and average sentiment score (4.5), indicating a favorable consumer response. Customer satisfaction stands at 85%, with high ratings for quality (4.7), installation (4.2), service (4.6), and logistics (4.8). By analyzing the three potential themes of negative text comments, the main reasons why consumers tend to have negative emotions (complaint points) after purchasing a washing machine are the quality issues (loud noise, low cleanliness, poor dehydration ability), poor service (poor attitude of installation technicians, poor after-sales service), and slow logistics speed of the washing machine [23]. Overall, consumer emotional tendencies directly correlate with goods and services, and businesses that address consumer concerns can help users generate positive emotions and eliminate negative ones.



(a)



(b)

Figure 7: Performance analysis. (a) Accuracy; (b) F1-Score

Figure 7 presents two performance metrics: accuracy over epochs and F1-score across varying data sizes for Model A and Model B. In the first graph, Model A shows faster learning, reaching 95% accuracy by the 10th epoch, while Model B peaks at 94%. Both models improve rapidly in the early epochs, stabilizing after the 7th. The second graph highlights F1-scores as data sizes increase from 1,000 to 10,000 instances. Model A consistently outperforms, starting at 0.70 and peaking at 0.88, while Model B starts at 0.68 and reaches 0.87, demonstrating both models' ability to generalize well.

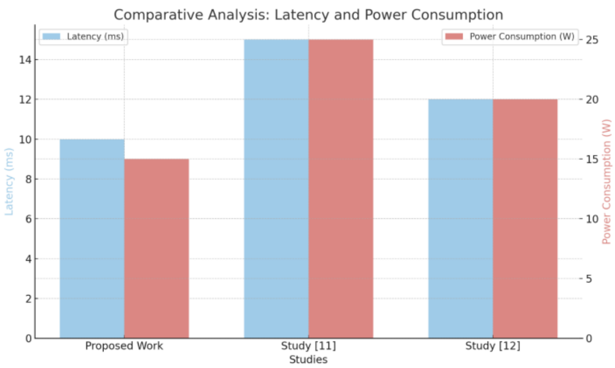


Figure 8: Comparative analysis of proposed model with existing studies [11], [12]

The proposed system demonstrates superior performance in both latency and power consumption. It achieves the lowest latency (10 ms) compared to Study [11] (15 ms) and Study [12] (12 ms), indicating faster communication response times. Additionally, it reduces power consumption to 15 watts, outperforming Study [11] (25 watts) and Study [12] (20 watts), highlighting its energy efficiency. Overall, the comparative analysis confirms that the proposed solution is more efficient and responsive than the existing studies for UAV-assisted communication.

5 Conclusion

This research utilized Chinese word segmentation to analyze user attention toward relevant attributes of drum washing machines and developed an adaptive planning model for audit robot patrol tracks. A control model for these patrol tracks was constructed by applying the discretization spatial planning method in conjunction with the RPA feedback correction algorithm. Based on the analysis of user text comments on drum washing machines from JD Mall, we offer several recommendations for sellers. These include prioritizing product quality as a key factor in attracting and retaining customers, investing in research and development to enhance both product performance and aesthetics, and improving the overall quality of installation personnel and service teams. Collaborating with local distribution and logistics companies ensures safe and timely delivery, which is crucial for customer satisfaction. Furthermore, leveraging brand value by promoting technological innovation and showcasing the full spectrum of product benefits can help attract and retain customers. Future work will focus on integrating advanced natural language processing techniques for a more nuanced analysis of customer sentiment in-text comments. Additionally, exploring the application of machine learning algorithms to predict consumer preferences and trends based on historical e-commerce data will further refine our understanding of market dynamics.

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