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MODELS FOR IDENTIFYING CONSUMER OPINIONS USING DIGITAL TECHNOLOGIES IN E-COMMERCE ACTIVITIES

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Abstract: The rapid development of digital technologies has significantly transformed e-commerce platforms, allowing users to interact and share opinions about products and services. Customer reviews play a crucial role in assessing product quality and guiding purchase decisions. However, due to the subjective nature and large volume of feedback, analyzing consumer opinions is complex and requires automated models. This study proposes a model for evaluating customer satisfaction using digital technologies, incorporating numerical ratings, likes/dislikes, and textual sentiment and topic analysis. Data collected from Alibaba reviews of Mac, Windows Surface, Asus, and Samsung laptops were analyzed using Principal Component Analysis (PCA) to determine factor weights and overall satisfaction scores. The proposed approach enables businesses to identify product strengths and weaknesses, improve service quality, enhance marketing strategies, and strengthen brand–customer relationships. Integrating sentiment analysis with AI and chatbots also promises more personalized customer interactions and higher satisfaction in digital commerce.

Keywords: E-commerce, Customer Feedback, Sentiment Analysis, Principal Component Analysis (PCA), Digital Technologies, Review Normalization, Consumer Satisfaction, AI Chatbots

Introduction

The rise of digital technologies has transformed the way consumers interact with products and services, leading to the proliferation of e-commerce platforms. These platforms serve not only as marketplaces but also as channels for sharing consumer opinions. Customer reviews, ratings, and feedback provide valuable insights into product performance, service quality, and overall consumer satisfaction. Businesses increasingly rely on this data to improve offerings, enhance marketing strategies, and gain a competitive advantage.

Despite their importance, analyzing reviews is challenging due to their subjective nature, potential bias, and sheer volume. Negative reviews, fake reviews, and contradictory opinions complicate the process of understanding true customer sentiment. Consequently, automated models using digital technologies, such as data scraping, normalization, and sentiment analysis, are essential for efficient and accurate assessment of consumer opinions.

This research presents a model integrating numerical ratings, user feedback (likes/dislikes), and textual analysis to evaluate customer satisfaction with laptops on Alibaba. The model employs Principal Component Analysis (PCA) to determine the contribution of different factors and calculates a final satisfaction score. Additionally, the study explores how AI-based sentiment analysis and topic modeling can further enhance insights into customer opinions, enabling companies to respond effectively and personalize interactions.

Today, the rapid development of digital technologies and their growing demand among users have led to the emergence of various e-commerce platforms. Through these platforms, users interact and exchange opinions with one another [1]. Such sites can be viewed as spaces for

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organizations to conduct marketing activities and gather consumer feedback. One of these types of resources is e-commerce platforms designed for publishing product or service reviews. There are numerous services that allow customers to express their opinions about a product or service and evaluate it based on a certain rating scale. Such feedback makes it possible to identify the strengths and weaknesses of consumer experiences, work with a wide range of product categories, and improve service quality.

The popularity of feedback-based resources can be explained by the tendency of potential customers to save financial resources and obtain high-quality goods or services. However, these services can also be used to publish negative information about competitors or to post purchased positive reviews. Moreover, due to the subjective nature of reviews, the information may be contradictory. These factors make the analysis of feedback and the determination of the actual quality of products or services a complex task that requires working with large volumes of data. Therefore, models and software solutions are being developed to automate the process of evaluating and interpreting consumer feedback.

The conducted analyses show that many researchers have studied consumer opinions in e-commerce and their impact on sales, as well as assessed and analyzed such feedback using various approaches and models. The following are some of the notable studies:

• In the research by Ghose and Ipeirotis, the impact of consumer feedback on sales volume was thoroughly studied. The researchers proposed two innovative approaches for assessing the expected usefulness of reviews and predicting sales volume. This analysis focuses on determining the real value of consumer feedback on e-commerce platforms, emphasizing that customer comments have a significant impact on commercial success [2].

• In the study conducted by Ho-Dac, Carson, and Moore, a regression model was applied to analyze the impact of positive and negative feedback on sales volume. This research considered various factors affecting sales, including brand popularity, product price, and advertising expenses. The findings show that not only positive reviews matter, but negative feedback can also adversely affect sales [3].

• In the study by Zhao, Jiang, and Su, the impact of organizational responses to negative reviews on consumer trust and purchase intentions was analyzed. The research highlights the role of response strategies in shaping consumers' attitudes toward the organization and how these attitudes influence future purchasing decisions [4]. This approach provides organizations with opportunities to build stronger relationships with consumers through effective management of negative feedback.

In addition, Zhao, Stylianou, and Zheng evaluated the social impact of anonymous reviews. Although anonymous feedback is often considered unreliable, it can still exert significant influence on social networks and e-commerce platforms [5].

Similarly, Gafni and Gola examined the effect of negative reviews in social networks. Their study analyzed how the spread of negative feedback affects consumer purchasing decisions [6].

Furthermore, Mohammadi and Malik conducted research on user activity, the usefulness of reviews, and their influence. This study suggests that reviews from active users are generally taken more seriously and can influence the decisions of other consumers [7].

The overall process of analyzing consumer feedback on e-commerce platforms consists of three key stages: data collection, data processing, and data analysis [8]. Each of these stages plays an important role in converting collected data into useful analytical results. The general structure of this process is illustrated in the diagram below

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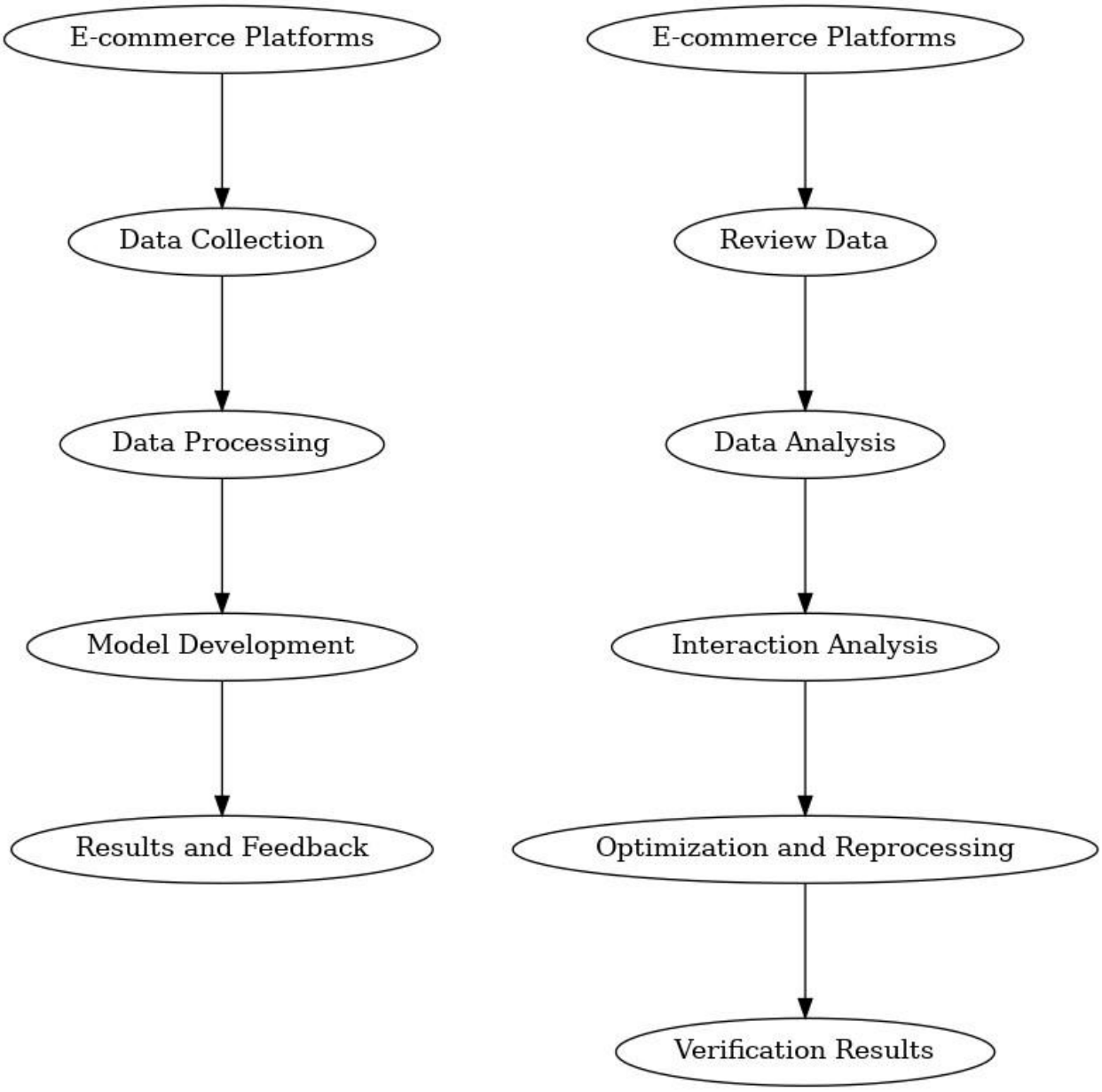

Figure 1. The Process of Analyzing Customer Reviews.

This process illustrates how customer review analysis is carried out step-by-step. Sentiment analysis is usually used to determine users' attitudes toward a product or service. The figure consists of two parts: the first part shows the stages of data collection, processing, and model development. The second part demonstrates the analysis and verification performed based on the obtained data. Each stage, particularly the optimization and reprocessing phases, is crucial for ensuring the accuracy of the results.

In our study, an automated model was developed to evaluate customer satisfaction/sentiment levels. The model uses reviews as the primary data source, applies Principal Component Analysis (PCA), normalizes review scores, and assigns weights to various factors. The analysis is demonstrated using Mac, Windows Surface, Asus, and Samsung laptops sold on Alibaba, and we present the effectiveness of the model in assessing customer satisfaction.

With the rapid growth of e-commerce platforms such as Alibaba, understanding customer satisfaction has become increasingly important. Particularly for high-value products like laptops,

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customers tend to rely on online reviews when making purchasing decisions. Customer reviews directly reflect user experiences; however, the large volume and subjective nature of feedback make analysis difficult.

Principal Component Analysis (PCA) is used to reduce complex datasets while retaining the most significant information. PCA identifies variance within the data and reduces high-dimensional datasets to several principal components. In customer satisfaction evaluation, PCA makes it possible to integrate various factors (ratings, likes, dislikes) to derive an overall satisfaction indicator.

In this study, data related to Mac, Windows, Asus, and Samsung laptops from the Alibaba platform were used. Web scraping technology was applied to collect the dataset. Using the Python programming language along with Selenium and BeautifulSoup libraries, information was automatically extracted from web pages (Figure 2).

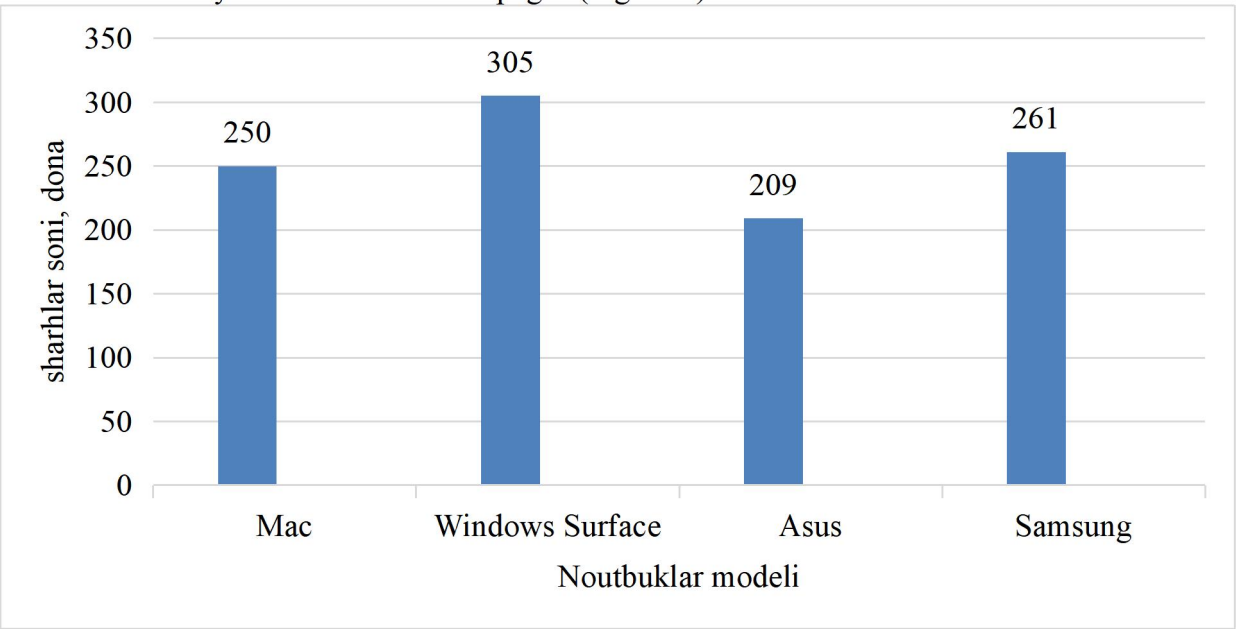

Figure 2. Reviews Collected via Web Scraping for Laptop Models

Web scraping technology offers the following advantages:

- **Data Reliability:** Real user-generated reviews are collected, providing more reliable and valuable information compared to artificially created data.

- **Speed and Automation:** It enables the collection of large volumes of data in a short period of time. This process is much more efficient and less labor-intensive than manual data collection.

- **Continuous Updating:** New reviews and data on websites are updated regularly. Each scraping operation allows real-time data refresh, which is essential for ongoing analysis.

Accordingly, the total score **Rl** for each review provided for a laptop is calculated using the following formula:

$$R_l = U_l - H_l (1)$$

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Where:

- **Likes (U):** Number of likes received by the review.
- **Dislikes (H):** Number of dislikes received by the review.

For each review, a total evaluation score is calculated, and these reviews are categorized into positive (rating 4 or 5), neutral (rating 3), and negative (rating 1 or 2) groups.
Rating (V): A score from 1 to 5 assigned by the customer.

The next step groups reviews for each laptop model based on their ratings and calculates the overall review score. The review scores indicate how useful users found the review. The grouped review scores for different laptop models are shown in **Table 1**.

To compare review scores across different laptops, the scores are normalized using the following formula:

$$R_I^* = \frac{R_I - R_{min}}{R_{max} - R_{min}} (2)$$

Here, **R_min** and **R_max** represent the minimum and maximum review scores for each laptop. This normalization distributes the review scores on a scale from **0 to 1** (Table 2).

Table 1

Grouping of Laptop Reviews

Review	**Score (V)**	**Likes (U)**	**Dislikes (H)**	**Total Score (R)**	**Classifier**
Mac					
1	5	10	1	9	Positive
2	4	8	2	6	Positive
3	3	5	3	2	Neutral
4	2	4	6	-2	Negative
5	1	3	7	-4	Negative
…	…	…	…	…	…
Windows Surface					
1	5	15	3	12	Positive
2	4	12	4	8	Positive

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Review	Score (V)	Likes (U)	Dislikes (H)	Total Score (R)	Classifier
3	3	7	5	2	Neutral
4	2	6	8	-2	Negative
5	1	4	10	-6	Negative
…	…	…	…	…	…
Asus					
1	4	13	2	11	Positive
2	4	10	3	7	Positive
3	3	6	5	1	Neutral
4	2	5	7	-2	Negative
5	1	4	8	-4	Negative
…	…	…	…	…	…
Samsung					
1	5	18	3	15	Positive
2	4	14	5	9	Positive
3	3	8	6	2	Neutral
4	2	7	10	-3	Negative
5	1	6	12	-6	Negative
…	…	…	…	…	…

Table 2. Normalized Review Scores for Laptops

Review	Normalized (Mac)	Score	Normalized (Windows S)	Score	Normalized (Asus)	Score	Normalized (Samsung)	Score
1	1		1		1		1	
2	0.833		0.778		0.733		0.789	

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Review	Normalized Score (Mac)	Normalized Score (Windows S)	Normalized Score (Asus)	Normalized Score (Samsung)
3	0.5	0.444	0.333	0.444
4	0.167	0.222	0.133	0.167
5	0	0	0	0
…	…	…	…	…

After normalization, the sums of positive, neutral, and negative reviews for each laptop were calculated:

$$S_p = \sum_{j=1}^{n_p} R_j^* \quad (3)$$

$$S_i = \sum_{j=1}^{n_i} R_j^* \quad (4)$$

$$S_n = \sum_{j=1}^{n_n} R_j^* \quad (5)$$

Where:

- n_p, n_i, n_n represent the number of positive, neutral, and negative reviews.

For the **Mac** laptop:

- $S_p = 1.833$
- $S_i = 0.5$
- $S_n = 0.167$

Other laptops are calculated similarly (shown in Table 3).

Table 3

Summary of Review Data

Product Name	Sum of Positive Reviews (S_p)	Sum of Neutral Reviews (S_i)	Sum of Negative Reviews (S_n)

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Product Name	Sum of Positive Reviews (S_p)	Sum of Neutral Reviews (S_i)	Sum of Negative Reviews (S_n)
Mac	1.833	0.5	0.167
Windows Surface	1.778	0.444	0.222
Asus	1.733	0.333	0.133
Samsung	1.789	0.444	0.167

Principal Component Analysis (PCA) was applied to the dataset to determine weight coefficients for different factors (ratings, likes, dislikes). The weights reflect the importance of each factor in determining overall customer satisfaction:

$$w_t = \sum_{r=1}^{m} P_{t,r} \cdot d_r \quad (6)$$

Where:

- $P_{t,r}$: factor loading for variable $t$and component r
- d_r: variance explained by component r
- m: number of principal components

The resulting weights were:

- $w_1 = 0.5$: average rating
- $w_2 = 0.3$: sum of positive reviews
- $w_3 = 0.1$: sum of negative reviews
- $w_4 = 0.1$: sum of neutral reviews

The average rating is calculated as:

$$L = \frac{\sum_{i=1}^{n} V_i}{n} \quad (7)$$

Normalized average rating:

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$$L^* = \frac{L - L_{min}}{L_{max} - L_{min}} (8)$$

Finally, the overall satisfaction score $M_k$is calculated as:

$$M_k = L_k^* \cdot w_1 + S_p^* \cdot w_2 + S_n^* \cdot w_3 + S_i^* \cdot w_4 (9)$$

Final Results:

Laptop	**Final Satisfaction Score** M
Mac	**0.866**
Windows Surface	**0.8496**
Asus	**0.8165**
Samsung	**0.8478**

Table 7

Analysis of the Results

Laptop	**Final Satisfaction Score**
Mac	0.866
Windows	0.8496
Asus	0.8165
Samsung	0.8478

The Mac received the highest score due to a greater number of positive reviews and fewer neutral/negative reviews.
Windows and Samsung show similar scores: although they have many positive reviews, the presence of negative reviews slightly reduced their final results.
Asus received a slightly lower score because the number of positive reviews was insufficient, and negative reviews had a noticeable impact on the overall rating.

In the next stage of research, we will explore how the customer satisfaction/sentiment model can be further improved by performing textual analysis of the reviews (see Figure 3). This model can provide valuable insights into customer emotions, review topics, and the satisfaction rating derived from them.

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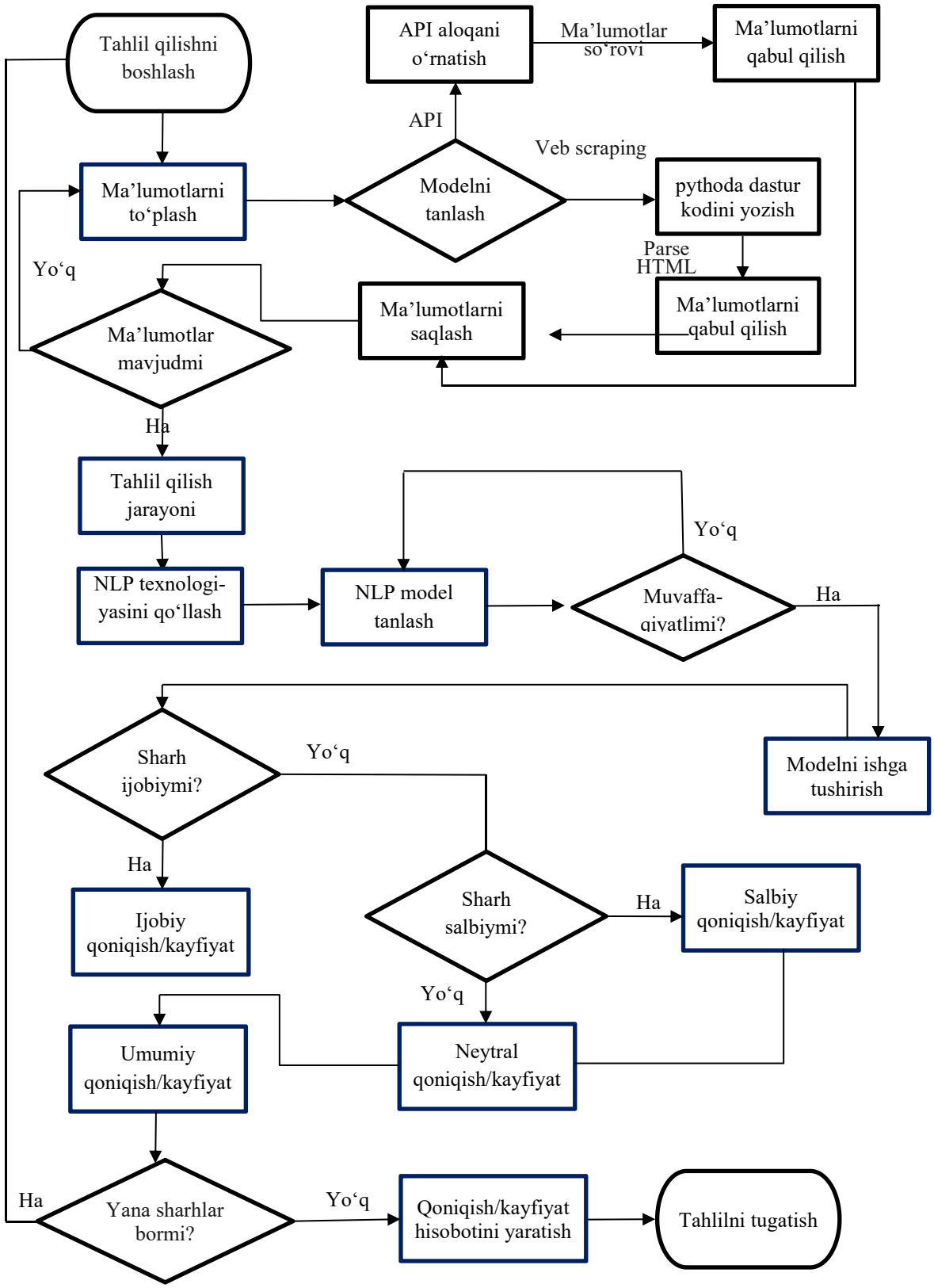

3-rasm. Qoniqish/kayfiyat modelini takomillashtirilgan algoritmi[1]

[1] Manba: Muallif ishlanmasi.

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Technologies for collecting reviews through sentiment analysis in e-commerce are becoming one of the most promising directions. One of the major upcoming innovations is the integration of sentiment analysis with artificial intelligence-based chatbots. This means that when a customer interacts with a chatbot, the chatbot will not only understand the words but also recognize the customer's emotional tone and respond in a more human-like manner. This improves the speed of customer support and increases user satisfaction.

In addition, companies are now using sentiment analysis data to create personalized advertisements. As a result, the advertisements shown to users match their individual interests, increasing their emotional connection with brands.

Another important direction is the deeper integration of sentiment analysis into product development processes, helping new products better align with customer needs. This leads to increased customer satisfaction and stronger loyalty. Machine learning algorithms play a crucial role here, allowing sentiment analysis models to adapt to changes in language trends and customer behavior in real time.

Sentiment analysis is also becoming more widely applied in voice-based technologies, as voice assistants and voice searches are increasingly used in daily life. Furthermore, more companies are paying attention to sentiment analysis to evaluate customer emotions across multiple platforms such as social media, email, and customer support channels. In the future, the combination of predictive analytics and sentiment analysis will enable companies to anticipate customer behavior and trends more accurately.

The integration of textual review analysis into customer satisfaction or sentiment models is carried out in several stages:

1. **Review Collection and Cleaning**: Review text data is collected using Python libraries such as BeautifulSoup and Selenium. Unnecessary characters such as HTML tags, emojis, and special symbols are removed. This improves data quality, speeds up computation, and ensures greater accuracy.
2. **Sentiment Analysis**: Tools such as VADER or TextBlob are used to automatically classify each review as positive (+1), neutral (0), or negative (-1). This reduces subjective errors that occur when human evaluators interpret emotional tone.
3. **Topic (Aspect) Analysis**: Key product features—such as performance, battery life, or display quality—are identified and analyzed separately. This helps determine which aspects customers value most and which areas require improvement.
4. **Integration of Sentiment and Topic Data into a Unified Model**: The sentiment scores and topic-based evaluations are combined and normalized, then incorporated into an overall sentiment model. Principal Component Analysis (PCA) or similar statistical methods are used to assess the contribution of each factor to overall customer satisfaction.

The final satisfaction score is calculated as:

$$M_k = L_k^* \cdot w_1 + S_p^* \cdot w_2 + S_n^* \cdot w_3 + S_i^* \cdot w_4 + S_{sent} \cdot w_5 + S_{topic} \cdot w_6$$

where **S_sent** represents the overall emotional tone of the reviews, and **S_topic** represents scores based on specific product-related topics. w_5 and w_6 are the corresponding weight coefficients.

Example of sentiment analysis on a review:

"*The laptop works well, but its battery drains quickly.*"

- "The laptop works well" → positive sentiment (+0.8)
- "Battery drains quickly" → negative sentiment (-0.5)

Sentiment score: (0.8 − 0.5) / 2 = 0.15 → slightly positive overall.

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Topic analysis identifies:

- Performance → positive
- Battery life → negative

This example shows how sentiment and topic analysis provide detailed insights into product strengths and weaknesses.

In conclusion, this research proposed a customer satisfaction evaluation model that considers not only numerical ratings but also the textual content of customer reviews. Unlike traditional methods, this approach accounts for the usefulness of reviews (likes and dislikes) and applies normalization and PCA to derive weighted impact factors.

Using digital technologies to analyze consumer opinions allows e-commerce platforms to better understand customer needs and improve service quality. Automated review collection and analysis helps identify product strengths and weaknesses, supports more accurate sales forecasting, enhances marketing strategies, and strengthens brand–customer relationships.

The integration of sentiment analysis with AI and chatbots will lead to more personalized customer communication and improved digital service experiences. This approach represents a significant innovation in the development of the digital economy.

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