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# Data-Driven User Personas in Requirement Engineering with NLP and Behavior Analysis

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***Abstract*—As technology rapidly evolves, software development faces growing complexity, requiring adaptation to dynamic user expectations. This study addresses a critical gap in the existing literature by integrating behavioral data and sentiment analysis into the user persona development process within the requirement engineering framework. The primary objective is to create more accurate and representative user personas that better guide software design and development. To achieve this, the research employs advanced Natural Language Processing (NLP) techniques to systematically analyze extensive behavioral and sentiment data collected from social media platforms. The integration process involves segmenting user data into behavioral patterns and emotional states, which are then synthesized to develop nuanced user personas. These personas are expected to significantly improve the accuracy of user requirements, leading to enhanced software performance, increased user satisfaction, and greater development efficiency. The target application area for this research is mobile telecommunications, where precise user understanding is critical. The results indicate that this approach not only refines the traditional persona method but also addresses the evolving needs of users more holistically. By advancing the methodology for user-centered design, this study contributes to the broader field of requirement engineering. Future research will validate and refine this approach across diverse domains, ensuring its adaptability and effectiveness in different contexts. This paper thus has the potential to make a significant impact on how user personas are developed and utilized in software engineering.**

***Keywords*—Requirement engineering; user persona framework; data-driven persona; natural language processing.**

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## I. Introduction

Persona, as a tool for understanding target user groups, has been broadly utilized in various domains such as software development, healthcare, e-commerce, marketing, and system design, and this methodology has remained stable for several decades [1]. The rapid evolution of technology has significantly increased the complexity of software development, creating a pressing need for systems that can effectively adapt to users' changing expectations. While valuable, traditional user persona construction methods often fail to capture the depth of user behaviors and emotional needs, leading to a gap in accurately understanding and predicting user requirements [2]. This study seeks to bridge this gap by integrating behavioral data and sentiment analysis into the user persona development process, thereby enhancing the precision and effectiveness of requirement engineering.

The goal of this project is based on the data-driven personas approach to create a new method that combines profiling segmented users, user behavior data, and user emotion data. To guide this research, the following specific questions are formulated:

a. How can behavioral data and sentiment analysis be effectively integrated to develop more accurate and representative user personas?
b. What impact does integrating these data sources have on the quality of user requirements and the overall efficiency of software development?
c. How can the developed user personas be applied within mobile telecommunications to validate their effectiveness in real-world scenarios?

This Obtain more accurate user needs and express them more clearly to users. The main goals are:

a. To construct a model that integrates emotional data analysis into data-driven behaviors.
b. To design an interface interaction method that automatically generates user segments and profiles

structured by NLP technology and analyzes representative persona characteristics.

c. Based on the method provided above, the research will design a system for mobile telecommunications to verify the usability of our method. The effectiveness of the model will be measured by comparing the consistency of the needs predicted by the model with the actual feedback on users' needs.

This project's scope centers on the methodology of software requirements, especially the application of these methods in the stages of requirement gathering.

This study employs advanced Natural Language Processing (NLP) techniques and behavior analysis to analyze user data collected from social media platforms systematically. The methodology involves:

a. Collecting extensive user behavior and sentiment data from platforms like Twitter or Weibo.
b. Applying NLP techniques to process and categorize this data, focusing on identifying key behavioral patterns and emotional expressions.
c. Integrating these insights to create detailed, data-driven personas that reflect users' behavioral tendencies and emotional states.
d. Validating these personas through their application in the design and development of a mobile telecommunications system, where the accuracy of user requirements and the efficiency of development processes will be assessed.

The persona framework in user experience design and human-computer interaction refers to methods and tools used to understand and address user needs. The essence of crafting detailed and holistic personas in Human-Computer Interaction (HCI) and User-Centered Design revolves around precisely depicting users varied and intricate behaviors and requirements. During the requirements analysis phase, data-driven approaches aim for more comprehensive and objective user requirement information.

However, Data-driven personas face numerous challenges. Salminen [3] showed that the misconceptions by clients and improper method application to data that is often cluttered, incomplete, or lacking depth. The core issues are usability concerns that undermine their practical application. Salminen [3] also said that the transparency of the persona creation process is crucial for user trust, yet this clarity often eludes users of data-driven personas.

Even though emotion is becoming predominant in design, Requirements engineers often overlook emotional needs in system design, leading to less user-friendly systems [2]. Most existing solutions are not designed with people's emotional goals, leading to a lack of adoption, engagement, and technology failure [4]. The mixed effects of including numbers in data-driven persona development underscore the need for innovative methods to balance numerical data's informative value with user-friendly designs to maintain persona effectiveness and credibility [2]. Jung [3] mentioned a crucial need for innovative methods in developing and presenting DDPs (Data-Driven Personas).

The evolution of software complexity necessitates a profound understanding of system outputs, a challenge highlighted by Droste [4], who underscores the difficulty professionals face in deciphering the reasons behind specific software behaviors. Furthermore, Singh [5] points out a significant gap in current software tools, which often overlook the human-centric aspects during design and modeling. Building on these insights, it is imperative to critique that while these works have laid the foundation for identifying the problems, they fall short of offering a holistic view that integrates technical and user-experience perspectives. My viewpoint stresses the need for an interdisciplinary approach encompassing the technical intricacies of software outputs and the nuanced understanding of user interactions.

### *A. Literature Review*

#### *1) Overview:*

The literature on user persona development, particularly within requirement engineering, reveals a growing shift toward data-driven methodologies [6]. This shift addresses the limitations of traditional personas shown in Fig. 1, which often fail to capture the depth and complexity of user behaviors and emotional needs. However, despite these advancements, significant gaps remain in integrating these methodologies effectively and understanding their broader implications for user-centered design.

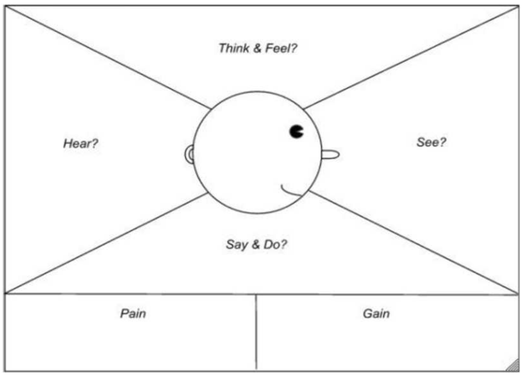


Fig. 1 User personas [6]

#### *2) Data-Driven User Persona Generation:*

A model is presented for enhancing transparency in Data-Driven Personas (DDP) through real system UI demonstrations [3]. They also showcased methods to integrate detailed breakdowns in personas, aiming to reduce stereotypical perceptions often associated with persona usage, as in Fig. 2. The DDR method involves constructing end-user personas, identifying target users, calculating commitments to personas, and determining release cases. The main challenge here is ensuring sufficient end-user data to keep accuracy.

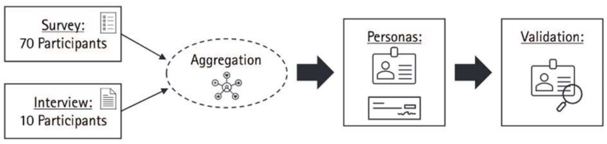


Fig. 2 Persona development and validation process [3]

Recent studies have focused on enhancing user persona generation through data-driven methods. The Automatic Persona Generation (APG) system uses social media data accessed via APIs to create personas from quantitative data

[7]. This method addresses the drawbacks of manually generated personas, which are often time-consuming and costly. Similarly, [8] improved upon this by integrating quantitative analysis of survey data, system log data, procedural personas, Latent Semantic Analysis (LSA), and discrete choice analysis. However, they noted that data-driven methods might struggle with deeply understanding user needs and avoiding biases.

*3) Requirements Collection and Analysis:*

The use of Natural Language Processing (NLP) in requirements engineering has been extensively explored. Salminen [9] reviewed 130 NLP4RE tools but found that only 17 were publicly available, indicating infrequent use of many novel NLP techniques. Miller [10] applied NLP to analyze requirement statements, employing lexical and syntactic features, ontology-based representation, and advanced embedding techniques. They highlighted the need for more adaptive syntactic processing. NLP was used to analyze social media review data, calculating emotional scores and using LDA for vocabulary mining [11]. However, this method may overlook other important evaluative dimensions.

Märtin in his study [8] mentioned that when emotions are taken into account while creating and adapting user interfaces, more intelligent and human-like interfaces can be designed. Data-driven personas have the potential to enhance user understanding by combining human empathy with analytical rigor [12]. The article referred to a conceptual of the persona to ensure that these data-driven personas remain relevant and effective, the positioning is reflected in Fig. 3 it shows the process of data analysis from the data-level to the analytics-level to the conceptual-level with the personas.

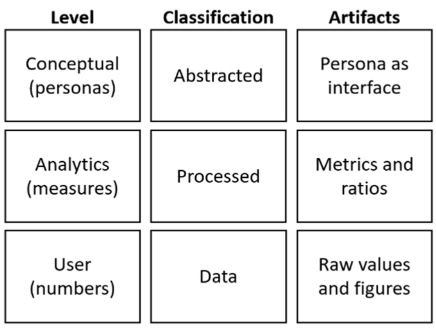


Fig. 3 From the data level to the analytics level with the personas [12]

*4) User Behavior Analysis:*

In the realm of user behavior analysis, McDonough [13] proposed PPSA, which protects user privacy by encrypting sensitive data while supporting aggregate queries for behavior analysis. The limitation is in maintaining data utility post-encryption. [14] suggested using data-driven personas as analytics tools to enhance user data utility and responsiveness, stressing the importance of balancing this approach with qualitative analyses and ethical considerations. [15] conducted a literature review on persona development, advocating for leveraging data volume to enhance interpretability while acknowledging the potential neglect of users' emotional needs.

The studies summarized in the table provide practical solutions to the challenges outlined in the problem statement. Enhancing the transparency of data-driven methods by [16], addressing emotional needs of users, and balancing numerical data with user-friendly designs [17] significantly improve the effectiveness of data-driven personas and requirements analysis. Additionally, [12] proposed a conceptual framework that leverages quantitative data and automated systems to enhance the utility and responsiveness of user data, while [18] introduced the PPSA scheme to ensure efficient data utilization by protecting privacy.

*5) Summary*

The reviewed literature underscores a collective movement towards more data-driven, nuanced personas that integrate both quantitative and qualitative data. However, a critical gap persists in the synthesis of these approaches. Specifically, while existing methods focus on enhancing efficiency and scalability, they often do so at the expense of depth and accuracy. Additionally, inconsistencies in how different studies handle data privacy and user diversity highlight the need for a more unified framework that can address these issues comprehensively. Future research should prioritize the development of integrated methodologies that not only automate persona generation but also ensure that these personas are reflective of the full spectrum of user behaviors and emotional needs, without compromising ethical standards.

## II. Materials and Method

Several methods are involved in this research, and some activities need to be considered. This section discusses the material and method for conducting the research.

### *A. Phase1: Literature Review*

This preliminary study employs a comprehensive literature review to gain insights into the project. This research aims to ascertain the necessity of optimizing role architectures and anticipate significant breakthroughs in human-computer interaction.

### *B. Phase2: Method and Model Construction*

Identifying the Scope and Attributes of Requirements, the research will conduct a thorough analysis to determine the scope and key attributes of the Persona tool in the context of the modern digital environment. This will involve an in-depth examination of the target user groups' behavior, preferences, and emotional needs.

### *C. Phase3: Design and Implementation System*

Our project endeavors to employ a system that leverages user empathy and a data-driven persona framework to interpret user requirements better. The initial framework, depicted in Fig. 4, includes the following components:

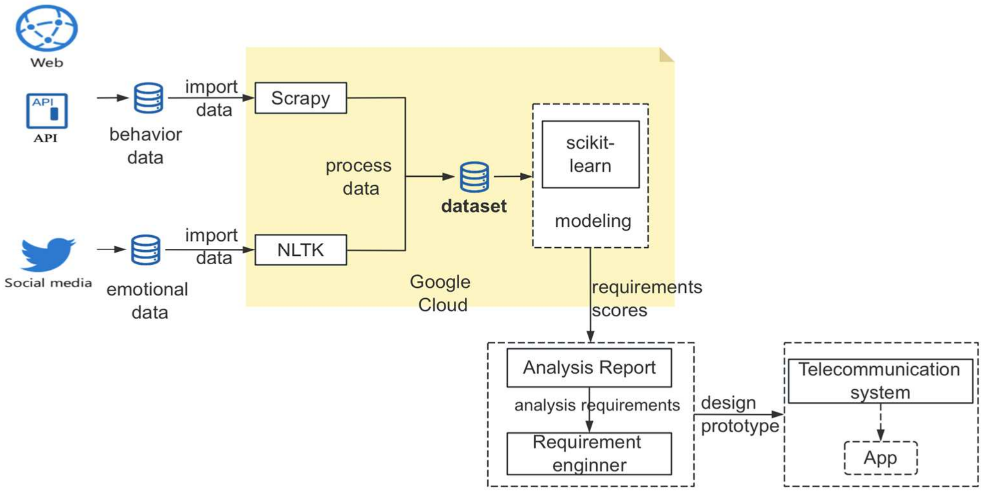


Fig. 4 The initial framework of the system

The data collection process involved extracting text data and collecting behavioral data. To extract text data, we used API access and web scraping techniques to collect user posts, comments, and reviews. Behavioral data collection captured user interactions, post frequency, and engagement metrics to understand user behaviors in the digital environment.

The analysis was conducted in two primary phases: NLP-based sentiment analysis and behavioral pattern analysis.

*1) NLP and Sentiment Analysis:*

a. Text Preprocessing: This will involve tokenization, stemming, and stop-word removal using Python's NLTK library.
b. Sentiment Scoring: Using sentiment lexicons and machine learning models, such as Support Vector Machines (SVM) or BERT, to classify user emotions.
c. Topic Modeling: Latent Dirichlet Allocation (LDA) will be employed to identify key themes in user-generated content.

*2) Behavior Analysis:*

a. Clustering Techniques: K-means clustering will be used to group users based on their behavior data, including activity frequency and types of interactions.
b. Pattern Recognition: Sequential pattern mining will be applied to identify common user pathways and behaviors across the dataset.

The integration of NLP and behavior analysis is central to this research. The sentiment analysis outcomes will be cross-referenced with behavioral data to create multi-dimensional personas. These personas will reflect what users say and how they behave. Specific techniques include:

a. Data Fusion: Combining sentiment scores with behavioral clusters to identify correlations between emotions and actions.
b. Persona Development: Creating personas based on synthesizing qualitative and quantitative data, ensuring they capture emotional and behavioral dimensions.

### *D. Phase4: Evaluation*

The evaluation will focus on both the usability of the developed personas and the accuracy of the requirement predictions derived from them. The evaluation plan includes:

*1) Usability Assessment:*

a. Metrics: System Usability Scale (SUS) and User Experience Questionnaire (UEQ) is utilized to assess ease of use and user satisfaction.
b. User Testing: A sample group of 50 participants will interact with the system, and their feedback will be collected through surveys and interviews.

*2) Accuracy Assessment:*

a. Metrics: Precision, recall, and F1-score will be calculated to evaluate the accuracy of the NLP models and behavior predictions.
b. Comparative Analysis: The accuracy of requirement predictions will be compared against actual user feedback and traditional persona methods.

Based on the new research method, this study will focus on creating models and methods, acquiring and analyzing requirements based on the model method, and implementing the final method results in the application system.

### *E. Material [Dataset]*

Based on the current version of the China Telecom app being utilized, the research collected user behavior data spanning from June 1, 2023, to December 1, 2023, as the primary data source for our research. The official China Telecom Weibo platform, boasting a substantial user base and extensive interaction data, currently engages approximately 160,000 active members. Consequently, the research utilized user-generated posts on the official China Telecom Weibo platform as our primary media data source. Employing Python 3.7, the research developed web scraping scripts to extract data, including user IDs, gender, age, location, and post content, during the specified timeframe.

Throughout this period, 4957 user posts were collected, out of which 4096 received replies, resulting in an interaction rate of 82.36%. During the data preprocessing phase, the research initially employed the Jieba library for text segmentation of the posts, as depicted in Fig. 5. Following this, we filtered out redundant and promotional posts to ensure the integrity of our dataset. Additionally, to enhance the sentiment analysis process, the research supplemented the dataset with sentiment lexicons based on the nuanced meanings of emojis commonly used in Weibo interactions.

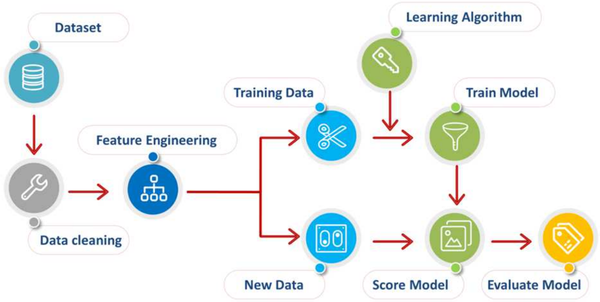


Fig. 5 Data preprocessing flow chart

## F. Data Processing

### 1) Model Research and Formation:

The formulation of tags stands as a pivotal step in constructing the USER-PERSONA model, representing highly condensed feature identifiers presumed to be set. This study's User-Persona tag system draws from both existing research methods outlined in Section II and the distinct user data element characteristics present in online telecommunications user communities. The construction process is delineated as follows: Initially, a comprehensive review of user profile constituent elements in literature pertinent to user models is conducted [19]. Existing studies predominantly structure user tag systems around dimensions such as basic information attributes, thematic feature attributes, behavioral attributes, and interest attributes [20], [21].

In China, official Weibo accounts refer to verified and legally effective microblogging platform accounts owned by enterprises or institutions. Therefore, by amalgamating the extraction of elements from online telecommunications user community characteristics, emotional attributes are introduced. This entails extracting elements from user posts and replies, comments, and user profiles. Finally, based on the extracted basic elements from real telecommunications users, irrelevant attributes are expunged, and basic information attributes, emotional attributes, thematic feature attributes, and behavioral attributes that resonate with the research objectives are curated. The resultant PERSON MODEL is illustrated in the accompanying Fig. 6.

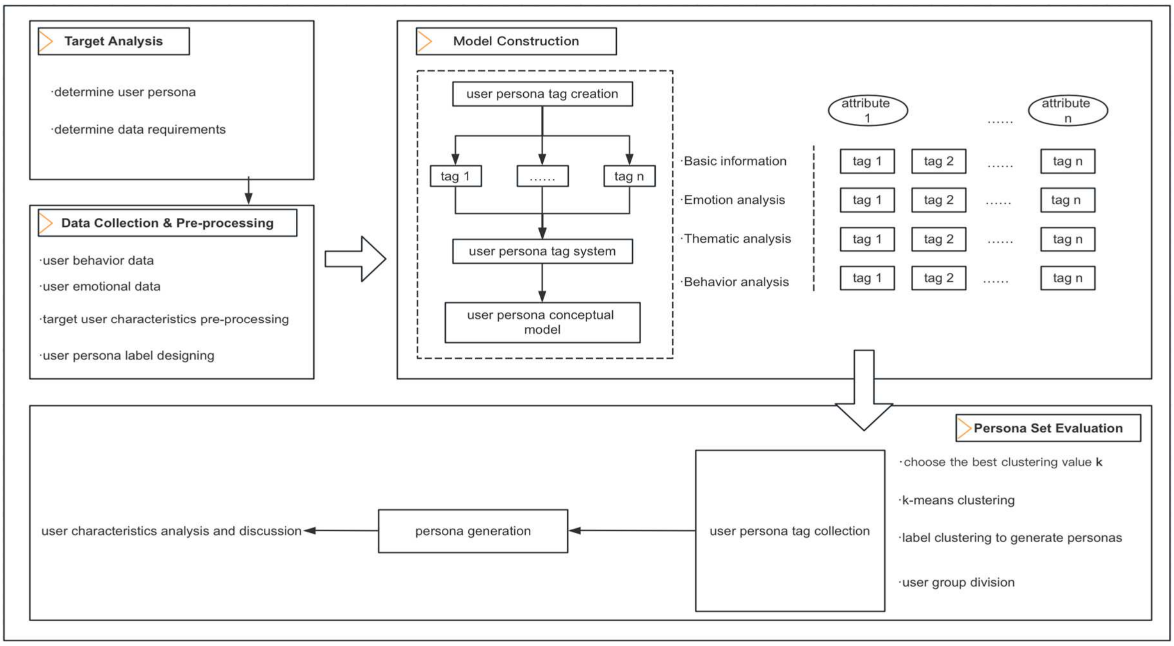


Fig. 6 New method conceptual framework

Establishing user persona tags based on the user profile indicator system will subdivide user profile tags into four dimensions. Basic information attributes describe attributes such as the user's age and gender, which can be directly generated without additional processing. Emotion attributes, theme feature attributes, and user behavior attributes require processing to obtain corresponding user tag attributes, as shown in Table I.

TABLE I
USER PERSONA LABEL SYSTEM

| Primary Indicator | Secondary Indicator | Explanation |
|---|---|---|
| Basic information attributes | Age; sex; region | Common criteria demographic characteristics |
| Emotion attributes | Emotion category: emotional types feature words; emotional intensity | Identify the strength of a certain emotion conveyed by users |
| Theme feature attributes | Theme categories; theme subcategory; theme feature words | The themes that media platform users pay attention |
| User behavior attributes | Total amount of user content generated; user influence; user activity | Social behaviors such as the total amount of user content generated, influence, and activity can identify the social network |

*2) Emotion Attribute Label Processing:*

*a. User identification*

In handling emotion attribute labels, the research first uses emotion words from the Dalian University of Technology emotion ontology as the basis. It constructs emotion seed words through the TF-IDF algorithm as supplements, ultimately forming a user emotion lexicon [21]. Secondly, specific calculations are conducted through the Sentiment Orientation-Pointwise Mutual Information (SO-PMI) algorithm [22]. Using the sentiment words' positive (Pwords) and negative (Nwords) orientations as reference terms, the research computes the value of each word $\partial 1$ concerning each word in these two lists, as shown in Equation (1):

$$\text{SO-PMI}(\partial 1)=\sum \text{PwordPMI}(\partial 1,\text{Pword})-\sum \text{NwordPMI}(\partial 1, \text{Nword}) \quad (1)$$

Where，$\text{SO-PMI}(\partial 1)>0$ indicates a positive sentiment orientation, and $\text{SO- PMI}(\partial 1)<0$ indicates a negative sentiment orientation. Finally, based on these sentiment-oriented feature attribute keywords extracted from the text, the research filter user texts: A. Users whose text in the main post contains emotion attribute words, such as "like", "dislike", or "annoyed". B. Users whose comments contain emotion attribute words. See the Table II below:

TABLE II
USER COMMENT EXAMPLES

| User nickname | User comment content |
|---|---|
| StarGazer89 | "I really appreciate the real-time data monitoring feature of the app, but it would be even better if there was an option to set a custom alert threshold to warn me when my data usage is close to the limit." |
| Wanderlust Wolf | "The personal information management in the app is very intuitive, but I hope there could be more privacy setting options, such as controlling which information is made public." |
| PixelPainter | "I like to check out promotional activities in the app, but the notifications are too frequent and sometimes feel a bit intrusive. It would be nice to have a feature that allows users to customize the frequency of notifications." |

*b. Emotional type classification and sentiment word recognition:*

Adopting the sentiment lexicon method, the research conducts sentiment analysis on posting and commenting texts of telecommunications users. This approach allows for a deeper understanding of emotional categories. The research utilizes a brand and product dictionary as the foundational lexicon for a granular analysis of emotional types and sentiment words. Subsequently, all posting texts are segmented based on the generated lexicon. Using Python and the Jieba library, the research performs emotional type classification and extracts key emotional features. After obtaining all postings' emotional types and feature words, only the most frequently occurring emotional feature words are selected as emotional labels, as illustrated in Table III.

TABLE III
EMOTIONAL CATEGORY SET HIGH-FREQUENCY EMOTIONAL FEATURE WORDS

| Emotion category | Emotional characteristic words |
|---|---|
| Needs/Expectations | Satisfied<br>Hope<br>Hassle<br>Appreciate<br>Expect |
| Inconvenience/Issues | Hassle<br>Expect<br>Dissatisfied |
| Security/Privacy | Secure<br>Privacy<br>Protect |
| Performance | Smooth<br>Optimize<br>Performance |
| User Experience | Beautiful<br>Intuitive<br>User-friendly |

*c. Sentiment intensity calculation*

Using a sentiment lexicon, the sentiment intensity of user texts is calculated. SnowNLP is a commonly used tool for Chinese sentiment analysis based on sentiment lexicons. It primarily conducts sentiment analysis on texts using a pre-trained corpus model, producing sentiment scores between [0, 1]. A score closer to 1 indicates a more positive sentiment, while a score closer to 0 indicates a more negative sentiment. SnowNLP library in Python is utilized to determine the intensity of user sentiments.

The main steps include: firstly, selecting a portion of positive and negative texts as training data to train the model, resulting in the model used in this study, sentiment.mar-shal.3; secondly, using the trained model to traverse all user texts and obtain sentiment intensity scores, manually annotating posting texts with abnormal return values; finally, classifying the sentiment intensity return values of user posting texts into 4 levels, ranging from weak to strong: weak emotional expression, low emotional expression, moderate emotional expression, high emotional expression [23]. The sentiment intensity levels of user posting texts are presented in Table IV.

TABLE IV
USER TEXT EMOTIONAL INTENSITY LEVEL

| Grade | Emotional intensity | Sentiment scores return value |
|---|---|---|
| Level 1 | Weak emotional expression emotional expression | 0-25 |
| Level 2 | General expression of emotion high emotional expression | 26-50 |
| Level 3 | Weak emotional expression emotional expression | 51-75 |
| Level 4 | General expression of emotion high emotional expression | 76-100 |

*3) Theme feature attribute label processing:*

*a. Topic category tags*

The LDA (Latent Dirichlet Allocation) topic model can cluster the text data contained in a large corpus into document-topic and topic-feature word clusters [24]. Therefore, this section utilizes the LDA topic model to explore topic category tags, and the calculation method is shown in Formula (2):

$$Pj(\omega i \mid ds)=P(\omega i \mid tj)*(tj \mid ds) \quad (2)$$

Formula (2) indicates that through two vectors (θd, φt), iterations are conducted according to certain probabilities. The topic words for telecommunications users are the intermediate vector layer. The model training adopts Gibbs sampling. After multiple training sessions, the ideal LDA model is eventually obtained. The topic-word labels are determined based on the topics in it.

*b. Subtopics and feature word labels:*

In this study, the text posted by users on the official microblog of the telecommunications company is taken as an example. LDA topic analysis is implemented using the sklearn library in Python, and it is found that telecommunications users mainly focus on topics such as payments, discounts, and packages. By continuously optimizing the topic categories concerning the content of microblog posts by telecommunications users, the final topics include Account Management, Billing Inquiry & Payment, Data & Call Services, Value-Added Services, Customer Support, and Promotions [25]. Regarding subtopics and feature words, LDAvis ranks the topic classification results by relevance. Three feature words are selected for each topic as user profile tags, ultimately forming a topic classification system. The topic categories, subtopics, and remaining words are grouped into subtopics, and feature words are attached.

*4) User behavior attribute label processing:*

*a. Labeling user-generated content volume*

Incorporating the distinctive traits of the "Hypertension" community on official Wei Bo, a method for computing information behavior attribute labels for User-Generated Content (UGC) is devised, outlined in Formula (3):

$$At=Gt+Ht \quad (3)$$

Here, Gt and Ht denote the user's engagement within topic threads, including the number of posts and replies made during a specific time segment t. At represents the total content generated by the user within this period.

*b. Determining user influence tags*

The calculation of the Influence (H) index offers simplicity and stability. The approach and algorithm for computing user influence labels are depicted in Formula (4):

$$I=\alpha\times ht+\beta\times hc+\gamma\times hl \quad (4)$$

In this equation, I represent the user's influence, while ht、hc, and hl signify the repost index, comment index, and like index of the user's engagement in posts. The coefficients α, β and γ serve as weights for ht, hc, and hl, respectively. The weight allocation strategy is as follows: behaviors with lower frequencies among reposting, commenting, and liking are assigned higher weights, indicating more significant time investment or more substantial user interest [26]. For instance, the average reposts, comments, and like counts for telecommunications user posts on the Weibo platform are 5.531, 24.432, and 15.570, respectively. Consequently, the weights assigned to α, β, and γ are 0.5, 0.2, and 0.3, respectively, as shown in Table V.

TABLE V
CONTENT GENERATED AND USER INFLUENCE

| Grade | Total amount of user content generated | A value | User influence | value |
|---|---|---|---|---|
| Level 1 | Content splash | [0, 8) | weak influence | [0, 3.3) |
| Level 2 | Low content output | [8, 15) | low impact | [3.3, 5.7) |
| Level 3 | General content output | [15, 23) | general influence | [5.7, 7.8) |
| Level 4 | High content output | [23, +∞) | core influence | [7.8, +∞) |

*5) Frameworks Design and Construction*

This study first extracts user features from public data of telecommunications users and then combines the specific characteristics of community posts on the telecommunications company's official microblog to obtain a user profile tag system and emotional user profile tags [27]. Finally, it constructs a conceptual model of telecommunications users based on user profiles, as shown in Fig. 7.

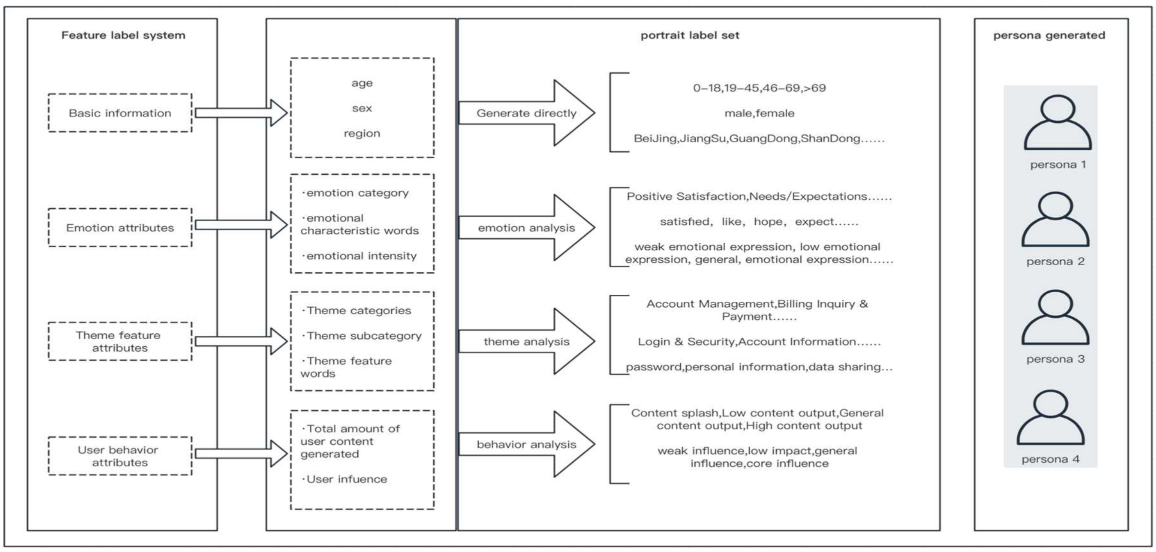

Fig. 7 Conceptual persona model

*6) Unsupervised Learning Model Construct End User Personas*

According to the collected telecom user dataset, the research employed the unsupervised K-means clustering method to categorize users into groups. In the clustering analysis, the research initially randomly selected K samples as cluster centers, then calculated the distance between each sample in the dataset and these cluster centers. Subsequently, each sample was assigned to the cluster whose center was closest, and the cluster centers were updated. This process was repeated until the cluster centers no longer moved, effectively classifying the user groups.

To enhance the granularity of user classification, the research utilized the fuzzy analytic hierarchy process to determine the weights of various indicators [28]. Additionally, the research invited experts in the field of library and information science to score the dataset, obtaining initial data for the telecommunication user profile based on online media communities [2]. Subsequently, the research employed the Python sklearn package to perform K-means clustering on the user profile dataset. When selecting the optimal number of clusters, the research utilized SSE (sum of squared errors) as the primary metric. The specific computation formula for SSE is as follows:

$$SSE=\sum k \sum |p-mi|2 \quad (5)$$

Through analysis of the elbow method graph depicting K and SSE, the research observed that the return on clustering diminished as K exceeded 4, with a deceleration in the rate of SSE reduction [29]. Consequently, the research determined that the clustering effect reached its optimum state when K equaled 4, shown in Fig. 8.

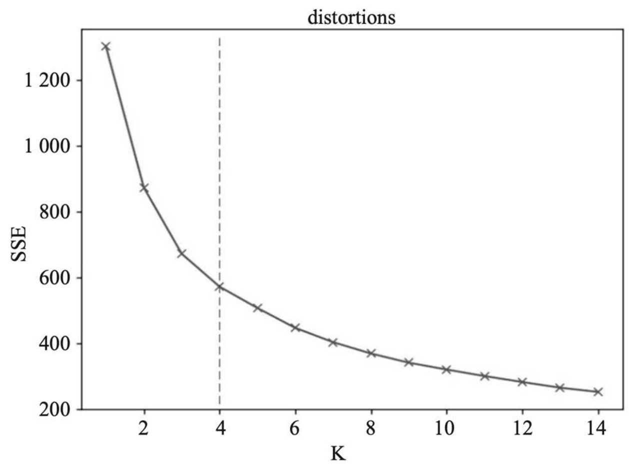

Fig. 8: Best clustering result

Based on this optimal clustering K value, telecom user profiles were successfully classified into four major categories: positive users, negative users, neutral users, and invalid users [30]. This classification enables us to better understand and serve different types of user populations. t

*7) Comprehensive User Scoring*

The calculation of user scores is done using a weighted average method. Basic information tags may have a lower weight because they are static; emotional tags may have a higher weight because they can reveal user satisfaction and loyalty; behavioral tags might have the highest weight because they disclose the actual engagement level of the user.

The weights for each category of tags are as follows:

a. Basic information tag weight: 0.1
b. Emotional analysis tag weight: 0.3
c. Behavioral analysis tag weight: 0.5
d. Thematic analysis tag weight: 0.1

The user's score can be calculated using a weighted average. For example, if a user's basic information score is 70, emotional analysis score is 90, behavioral analysis score is 60, and thematic analysis score is 80, then the user's composite score would be:

$$\text{Composite score} = (70 * 0.1) + (90 * 0.3) + (60 * 0.5) + (80 * 0.1) = 7 + 27 + 30 + 8 = 72.$$

Based on user scores, the needs of users with scores above 50 are analyzed to obtain the top 10 requirements and analysis them into the system requirement.

*G. Case Study: Telecommunication System*

*1) Requirement Analysis*

By analyzing the requirements, the following list of functional requirements and sub-functional requirements are obtained.

- *Functional Requirements*：

User Profile Analysis：Ability to collect user data and preferences.

1. Functionality to analyze spending patterns and service usage.
2. Features to create personalized data and call package recommendations.
3. Billing and Payments Enhancement：
   a. Historical comparison feature in billing inquiry.
   b. Support for multiple payment methods.
   c. Secure saving of user payment information.
   d. Customer Service Improvement Direct channels for live customer support.
   e. Queue management system for reduced wait times
4. Subscription Management：
   a. Reminder system for plan renewals.
   b. Automated notifications for renewal dates
5. Fault Reporting System Upgrade ：
   a. Stable image upload functionality for reporting faults.
   b. Streamlined process for reporting issues.

- *Non-Functional Requirements* ：

1. Performance Optimization：
   a. Compatibility tests on various devices.
   b. Code optimization for older devices.
2. Privacy Settings Enhancement：
   a. Additional privacy controls within the app.
   b. Compliance with data protection regulations.
3. Security Measures：
   a. Implementation of dynamic passwords and two-factor authentication.
   b. Regular updates to security protocols.
4. Subscription Management：
   a. Reminder system for plan renewals.

b. Automated notifications for renewal dates.

5. Data Visualization Tools:
   a. Dashboards with data visualization for service usage.
   b. Visual reports of user account activity.
6. User Guides and FAQs:
   a. Comprehensive and up-to-date user guides.
   b. FAQs.

*2) Use Case*

In this section, the use case demonstrates the functionality of the requirements generator component.

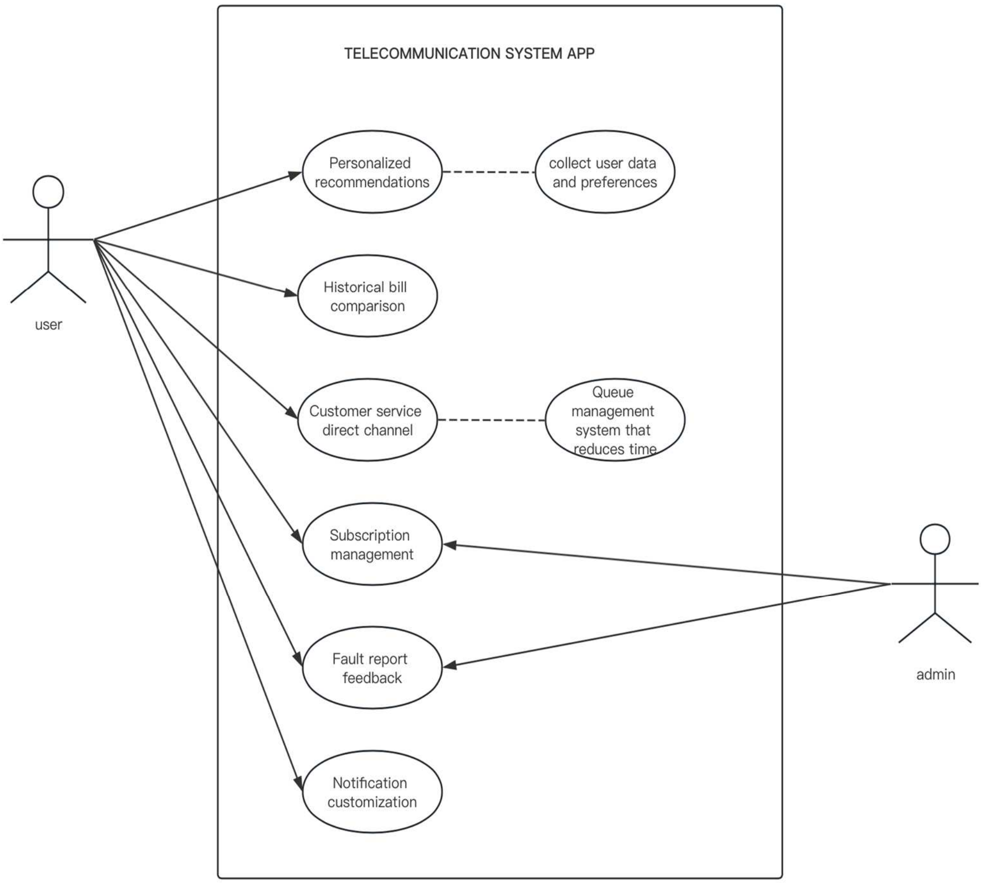


Fig. 9 Use case

This use case, shown in Fig. 9, aims to depict the graphic features available within the tool. Additional descriptions will clarify the processes by which users engage with the offered functionalities. In this section, the selected use case descriptions, such as User Profile Analysis, Billing and Payments Enhancement, and Implementation of Security Measures, will be explained.

*3) System Interface*

The tool's graphical user interface (GUI) enables users to interact with the framework's systems. GUI is a prototyping tool designed using Axure. Axure provides dynamic content, making it easier for developers to understand the interactive content required. In this area, the tool's graphical user interface (GUI) consists of key elements such as password verification, historical bill comparison, form content upload, image and upload subscription management, and user request form.

Fig. 10 shows one of the prototype implementations of requirements for historical bill comparison obtained according to the new method. Upon entering the application interface, users are greeted with a notification prompting them to check for any outstanding bills. This notification prompts users to tap on the "Bills and Payments" option to access detailed billing information.

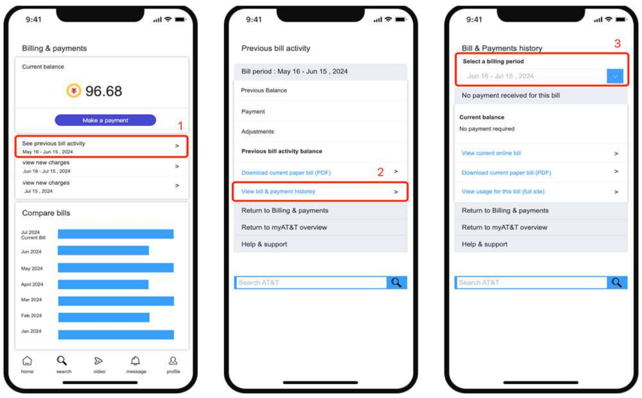


Fig. 10 Billing and payments enhancement interface

After selecting the "Bills and Payments" feature, the system prompts the user to log in. Once the credentials are entered and the "Billing History" option is selected, the system will respond within 3 seconds, displaying the user's billing history for the past six months. Users can peruse past bills and select a particular month's bill for a detailed comparison. The system contrasts the chosen bill against current and other historical bills, presenting an in-depth comparative analysis.

When the user decides to settle the most recent bill, the system offers a range of payment methods, including credit cards, debit cards, and online payment platforms. The user selects a payment method and opts to "Save as preferred method for future payments." After the payment details are confirmed, the system securely processes the transaction and displays a confirmation message of successful payment. Additionally, the system records the user's choice of payment method for future convenience.

### H. Evaluation

#### 1) User Research on Optimization Requirements:

The research will conduct a survey to compare the existing system with newly developed prototypes, targeting user groups identified through persona clustering and aligned with demand analysis. This comparison will evaluate usability, feature satisfaction, and personalization, focusing on system usage, page color schemes, and functionality. Participants, selected based on their representation of targeted user groups, will complete an online questionnaire. The study will validate user satisfaction with the new requirements using traditional user research methods, such as surveys, discussion forums, and focus groups, known for eliciting direct feedback.

- *Survey Design*

The Telecom Service User Satisfaction Survey will compare the operational experience between current and new systems, using Google Forms to gather feedback on usability, feature satisfaction, and personalized experience. The survey combines quantitative ratings with open-ended questions to obtain both statistical data and in-depth insights. Usability will be assessed using the System Usability Scale (SUS), a 10-item questionnaire providing an overall usability score for the system.

The 10 Questions for the existing system are as follows:

1. The functions of the existing system are simple to use.
2. I require much technical support to use the existing system.
3. The various functional modules of the existing system work well together.
4. The existing system is very stable during daily use.
5. The response speed of the existing system is satisfactory.
6. The interface design of the existing system is pleasant.
7. The existing system provides sufficient features to meet my needs.
8. It is easy to find the necessary functions in the existing system.
9. The notification and reminder features of the existing system are advantageous.
10. The user guides and help document of the existing system are detailed and helpful.

The ten (10) Questions for the Newly Designed Features are as follows:

1. The newly designed user profile analysis feature is convenient.
2. The billing and payments enhancement features in the new design are significantly improved compared to the existing system.
3. The new customer service improvement features effectively reduce wait times.
4. The reminder system in the new subscription management feature is very useful.
5. The upgraded fault reporting system makes it easier to report issues.
6. The notification customization feature in the new design meets my personalized needs.
7. The one-click export function in the new design greatly facilitates my operations.
8. The integrated network testing tool provides accurate network performance data.
9. The new community platform effectively promotes user interaction.
10. The enhanced privacy settings in the new design make me feel more secure using the system.

- *Sample Selection*

The study leveraged user behavior data collected from the China Telecom app and user interactions on China Telecom's official Weibo platform to conduct a user persona analysis. 4957 posts were gathered in six months, with an impressive 82.36% interaction rate.

- *Execute Research*

To conduct the research, the research has resolved to solely utilize online questionnaires for data collection, capitalizing on their convenience and extensive reach. The research intends to construct a comprehensive online survey comprising meticulously crafted questions to elicit feedback on users' experiences with current and new telecom systems. The questionnaire will feature diverse question types, from multiple-choice questions that facilitate rapid quantitative analysis to open-ended queries that capture richer user opinions.

#### 2) Expert Review:

Design the experimental process to ensure that it can test the model's ability to integrate and explain the four major data label sets. In this part, the research uses the Likert Scale [24] for evaluation metrics such as accuracy. The case study evaluates usability to quantitatively evaluate user personas.

- *Dataset Sample*

The dataset used for the experiment evaluates the user requirement model, incorporating test data derived from the system's existing user demographic information, processed emotional data, and thematic attribute tags. In this phase, assessment criteria based on user roles have been developed, including accuracy, completeness, interpretability, and transparency, to perform a quantitative evaluation of the user role model.

- *Participant Selection*

The experiment will be conducted with two seasoned developers and two requirements' engineers from the telecommunications industry. They will evaluate the user requirement model using quantified assessment metrics. Table VI below lists the basic information of the participants.

TABLE VI
EXPERT INFORMATION

| No | Expert Information |
|---|---|
| 1 | Name: Zhu Yan Jun<br>Experience: 10 years<br>Role: Senior Telecom System Developer |
| 2 | Name: Tian Wei Jie<br>Experience: 11 years<br>Role: Lead Telecom System Developer |
| 3 | Name: Liu Jing<br>Experience: 9 years<br>Role: Telecom System Developer |
| 4 | Name: Li Ya Xuan<br>Experience: 7 years<br>Role: Senior System Requirements Engineer |
| 5 | Name: Gao Ping<br>Experience: 5 years<br>Role: System Requirements Engineer |

- *Experimental Material Preparation*

The research can design a Likert scale-based questionnaire to evaluate the effectiveness of the sentiment model depicted in the provided diagram. This questionnaire will cover the model's key attributes, allowing experts to rate the performance of each attribute. Each attribute will be broken down into specific indicators, and experts will rate their satisfaction with each indicator.

Likert Scale Design

Evaluation Metrics:

1. Accuracy of Basic Information:
   a. Accuracy of Age Recognition
   b. Accuracy of Gender Recognition
   c. Accuracy of Region Recognition
2. Analysis of Emotional Attributes:
   a. Accuracy of Emotion Category Recognition
   b. Accuracy of Emotion Keywords Recognition
   c. Accuracy of Emotion Intensity Recognition
3. Analysis of Theme Features:
   a. Accuracy of Theme Category Recognition
   b. Accuracy of Theme Subcategory Recognition
   c. Accuracy of Theme Keywords Recognition
4. Analysis of User Behavior Attributes:
   a. Accuracy of Total User Content Generation
   b. Accuracy of User Influence Evaluation

For each evaluation metric, the following Likert scale will be used:

1 = Very Dissatisfied
2 = Dissatisfied
3 = Neutral
4 = Satisfied
5 = Very Satisfied

## III. RESULTS AND DISCUSSION

### A. Experimental Result

Based on the above verification results, this section summarizes the results of user feedback on the system and expert feedback on the model.

#### 1) Usability Analysis:

Usability refers to the quality of user experience when interacting with any software product. Furthermore, to test the suitability hypothesis of usability measurement, the research used the System Usability Scale (SUS) developed by John Brooke in 1986 on data from five randomly selected users from the surveyed users. The scale relies on a set of standard subjective ratings across three domains: usability, which indicates the user's perceived ease of use of the system; and satisfaction, which indicates how much the user enjoys using the system.

The result of the user experience is presented as shown in Fig. 11 and Fig. 12:

| User | Q1 | Q2 | Q3 | Q4 | Q5 | Q6 | Q7 | Q8 | Q9 | Q10 | X0=(Total Odd No - 5) | Y0=(25 -Total Even No.) | SUS = (X0 + Y0 ) * 2.5 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 2 | 4 | 5 | 2 | 1 | 5 | 4 | 5 | 4 | 3 | 16 | 12 | 70 |
| 2 | 4 | 5 | 3 | 3 | 1 | 5 | 4 | 2 | 4 | 5 | 18 | 16 | 85 |
| 3 | 4 | 3 | 4 | 5 | 4 | 3 | 5 | 1 | 4 | 3 | 16 | 10 | 65 |
| 4 | 4 | 2 | 5 | 4 | 4 | 1 | 5 | 2 | 5 | 3 | 18 | 13 | 77.5 |
| 5 | 4 | 5 | 4 | 3 | 1 | 3 | 5 | 2 | 4 | 5 | 19 | 15 | 85 |

Fig. 11 Existing system function SUS score

Each participant provides an individual SUS Score and a cumulative SUS Score. The grading scale is derived by computing the mean of all individual SUS Scores.

Average SUS Score = (70 + 85 + 65 + 77.5 + 85) / 5 = 76.5

| User | Q1 | Q2 | Q3 | Q4 | Q5 | Q6 | Q7 | Q8 | Q9 | Q10 | X0=(Total Odd No - 5) | Y0=(25 - Total Even NO .) | SUS = X0 + Y0 ) * 2.5 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 4 | 2 | 5 | 4 | 3 | 2 | 4 | 5 | 5 | 4 | 18 | 14 | 80 |
| 2 | 5 | 3 | 5 | 4 | 3 | 2 | 5 | 4 | 5 | 4 | 19 | 16 | 87.5 |
| 3 | 4 | 2 | 5 | 5 | 4 | 3 | 5 | 5 | 4 | 5 | 19 | 13 | 80 |
| 4 | 5 | 3 | 5 | 4 | 4 | 3 | 5 | 4 | 5 | 5 | 19 | 14 | 82.5 |
| 5 | 5 | 2 | 5 | 5 | 4 | 3 | 5 | 5 | 4 | 5 | 20 | 13 | 82.5 |

Fig. 12 New system function SUS score

Average SUS Score = (80 + 87.5 + 80 + 82.5 + 82.5) / 5 = 82.5

Therefore, the usability of the system functions designed based on the needs evaluated by the model can be obtained based on the SUS Score and compared with the existing system, the new design features are more acceptable to users.

#### 2) Expert Review Analysis

Five experts gave corresponding feedback and evaluation results based on the evaluation template during the model review meeting. The results of the five experts' ratings are as Table VII as follows:

TABLE VII
EVALUATION RESULT

| Evaluation Metric | Expert 1 | Expert 2 | Expert 3 | Expert 4 | Expert 5 |
|---|---|---|---|---|---|
| Accuracy of Gender Recognition | 5 | 4 | 4 | 5 | 5 |
| Accuracy of Region Recognition | 3 | 4 | 4 | 3 | 4 |
| Accuracy of Emotion Categories | 4 | 4 | 3 | 4 | 4 |
| Accuracy of Emotion Keywords | 3 | 3 | 4 | 3 | 3 |

For each evaluation metric, calculate the following statistics:

- Mean: Reflects the central tendency of the scores.
- Standard Deviation: Indicates the dispersion of the scores.
- Median: Represents the middle value of the scores, providing insight into the score distribution.

Example of data analysis, for the "Accuracy of Age Recognition" metric:

- Mean = (4 + 3 + 5 + 4 + 4) / 5 = 4.0
- Standard Deviation = sqrt [((4-4) ^2 + (3-4)^2 + (5-4)^2 + (4-4)^2 + (4-4)^2) / 4] = sqrt(2 / 4) = 0.707
- Median = 4

Similarly, calculate these statistics for each metric and summarize them in Table VIII:

TABLE VIII
EVALUATION STATISTICAL RESULT

| Evaluation Metric | Mean | Standard Deviation | Median |
|---|---|---|---|
| Accuracy of Age Recognition | 4 | 0.707 | 4 |
| Accuracy of Gender Recognition | 4.6 | 0.548 | 5 |
| Accuracy of Region Recognition | 3.6 | 0.548 | 4 |
| Accuracy of Emotion Categories | 3.8 | 0.447 | 4 |
| Accuracy of Emotion Keywords | 3.2 | 0.447 | 3 |
| Accuracy of Emotion Intensity | 4.2 | 0.447 | 4 |
| Accuracy of Theme Categories | 4.6 | 0.548 | 5 |
| Accuracy of Theme Subcategories | 4 | 0.556 | 4 |
| Accuracy of Theme Keywords | 3.6 | 0.548 | 4 |
| Accuracy of Content Generation | 3.6 | 0.548 | 4 |
| Accuracy of User Influence | 4.2 | 0.447 | 4 |
| **Average** | **78.91%** | **45.30%** | **81.81%** |

From Table VIII, the research shows that the average standard deviation of 45% indicates moderate variation in the ratings. It is neither high nor low, suggesting a certain degree of agreement among the experts but not complete consensus. The average mean of 78.91% and the average median of 81.81% indicate that the expert panel's review corroborates that the telecom system user persona model is adeptly designed and exhibits commendable accuracy.

### *B. Evaluation Result*

Through the above results, the research has analyzed user satisfaction with new features based on the existing system capabilities and assessed the usability of the optimized design requirements generated from the new model using the System Usability Scale (SUS) Score. And the research also calculated the overall sus score (Table IX):

TABLE IX
OVERALL SUS SCORE

| new system SUS | existing system SUS | Overall, SUS |
|---|---|---|
| 70 | 80 | 75 |
| 85 | 87.5 | 86.25 |
| 65 | 80 | 72.5 |
| 77.5 | 82.5 | 80 |
| 85 | 82.5 | 83.75 |
| 70 | 80 | 75 |
| 85 | 87.5 | 86.25 |

Average SUS Score = (75 + 86.5 + 72.5+ 80 + 83.75) / 5 = 79.5

The model was subjected to a multi-dimensional evaluation during an expert review meeting. Based on the results presented, the research can conclude that the demand design method produced by the new model, integrated with a Data-Driven Persona approach, possesses usability that satisfies 80% of users regarding user interface design and interactivity. The model's interpretability received the highest scores during the expert review process, indicating that its logic and processes are clear and comprehensible to developers. However, the review also underscored limitations in the model's completeness, aligning with user survey outcomes, suggesting that further enrichment of data and expansion of functionalities are necessary.

## IV. CONCLUSION

This research enhances user persona creation by introducing a data-driven model that integrates segmented profiling, behavioral data, and emotional analysis, providing a deeper understanding of user needs. Tested in a mobile telecommunications system, the model shows promise in bridging predicted and actual user requirements, improving user experience design. However, its effectiveness is limited by data quality, emotional analytics subjectivity, and scalability challenges. Future work should focus on diversifying datasets, refining emotional analysis with machine learning, cross-industry validation, and ensuring ethical data handling to enhance the model's practicality and applicability.


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