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Evaluating Usability and Clustering of SILCARE System for MSME Shipping: A Data-Driven Approach Using SUS and User Behavior Analysis

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Abstract

The SILCARE system is a digital logistics platform designed to optimize shipping operations for Micro, Small, and Medium Enterprises (MSMEs). This study evaluates its usability and user behavior patterns through System Usability Scale (SUS) assessments and clustering analysis. The research involved 100 SME users performing key system tasks such as registration, product management, and order confirmation. The SUS results showed a significant usability improvement, with the pre-test score of 74.5 (B grade) increasing to 90.25 (A grade) in the post-test, indicating enhanced user experience. User interaction data analysis revealed that registration took an average of 7.11 minutes, product addition 8.91 minutes, and order confirmation 5.15 minutes. Clustering using DBSCAN identified four distinct user groups, highlighting behavioral differences, where 37% of users struggled with complex tasks while 25% displayed balanced engagement. These findings inform targeted system improvements, such as simplifying workflows for new users and enhancing features for power users. The novelty of this study lies in integrating usability testing with behavior-driven clustering to refine a logistics platform tailored to MSMEs. By leveraging data-driven insights, the SILCARE system contributes to digital transformation in MSME logistics, improving operational efficiency and user satisfaction The paper explores the development process of the system, starting from the requirements gathering phase, where user needs were identified through extensive surveys and interviews with stakeholders. The iterative prototyping method allowed for the creation of an initial version of the system that was refined based on user feedback, ensuring that the final product met both functional and usability standards. The SILCARE system holds substantial promise for MSMEs, offering a digital solution for streamlining logistics and shipping processes and contributing to the overall success of small businesses.

Keywords: SILCARE, MSMEs, Logistics Management, System Usability Scale, User Clustering, Data Analysis

1. Introduction

Micro, Small, and Medium Enterprises (MSMEs) are essential drivers of economic development, playing a pivotal role in fostering economic growth and absorbing employment in many countries, including Indonesia. MSMEs represent over 99% of businesses in Indonesia, with a total of approximately 64.19 million MSMEs. They are responsible for employing 119 million workers, which constitutes around 97% of the national workforce in the business sector. These statistics highlight the significant contribution of MSMEs to the nation's economy, accounting for approximately 60% of Indonesia's GDP in 2019. However, MSMEs in Batam City face numerous challenges, particularly in the areas of shipping and promotion of their products. The role of MSMEs in promoting sustainable development through resource-efficient production and consumption is also critical for the country's broader economic sustainability goals [1]. As Indonesia continues to embrace globalization, local MSMEs must increasingly compete with international players in

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the global market. This necessitates a shift toward leveraging digital technologies to streamline operations and enhance competitiveness.

The digital revolution has significantly reshaped the global economy, fundamentally altering how goods are produced, distributed, and consumed. One of the most notable transformations has occurred in the e-commerce sector, which has enabled MSMEs in many countries to thrive by providing digital platforms that enhance their operational capabilities [2],[3].In this digital era, e-commerce is becoming an essential business strategy, particularly for small and medium-sized enterprises in developed countries [4]. The rapid advancements in information technology (IT) have facilitated this transformation, simplifying business operations and fostering economic growth [5].

Mobile technology, in particular, has proven to be a game-changer for MSMEs. Defined as devices that are internet-connected and provide users with mobility, mobile technologies enable MSMEs to expand their market reach and enhance operational efficiency. These mobile applications allow businesses to access services and manage operations on-the-go, regardless of location [6] . As such, mobile programming—especially on platforms like Android Studio—has become increasingly integral to MSME operations. Android Studio, an integrated development environment (IDE), supports the development of mobile applications, allowing for seamless integration of logistics and other business functions.

One promising approach to optimizing logistics operations for MSMEs is the use of clustering techniques. Clustering, such as K-means and hierarchical clustering, allows businesses to group similar entities based on shared characteristics, providing valuable insights into behaviors, patterns, and preferences. In the context of MSME logistics, clustering can be applied to segment MSMEs according to their usage patterns of logistics platforms, such as SILCARE. By clustering MSMEs based on their behavior data, it becomes possible to offer personalized shipping solutions that cater to each group's specific needs. Clustering behavior data allows for the identification of unique shipping patterns, preferences, and challenges, enabling the development of tailored solutions that improve efficiency, reduce costs, and enhance customer satisfaction. This approach is particularly valuable for MSMEs in Batam City, where shipping and logistics remain key challenges.

The primary aim of this research is to develop an integrated mobile-based logistics platform, SILCARE, designed to address the logistics challenges faced by MSMEs in Batam City. By leveraging advanced data science techniques, including clustering analysis of MSME behavior, the platform will enable real-time decision-making, ensuring that shipments are optimized in terms of cost and time. This research will contribute to enhancing the competitiveness of MSMEs by providing tailored logistics solutions that reduce shipping costs, optimize delivery times, and streamline the entire shipping process. Ultimately, the integration of behavior-based clustering into the SILCARE platform will play a critical role in empowering MSMEs to overcome logistical challenges and improve their overall business operations.

2. Literature Review

2.1. MSMEs and Their Role in Economic Development

The definition of MSMEs (Micro, Small, and Medium Enterprises) varies significantly between countries and even among different institutions within the same country. Different organizations, such as governments, financial institutions, and international agencies, provide varying thresholds to categorize businesses as MSMEs, depending on the context and specific criteria like revenue, number of employees, and asset size [7],[8],[9]. This inconsistency presents challenges in the accurate assessment and comparison of MSMEs across different regions.

MSMEs are a cornerstone of the economy in many countries, especially within the context of developing nations. MSMEs are recognized for their substantial contribution to poverty reduction and national economic development through job creation, innovation, and social integration. They play an essential role in fostering economic growth by stimulating local economies and offering entrepreneurial opportunities to underserved populations [10],[11]. In fact, MSMEs are among the largest employers in many low-income countries, providing livelihoods for millions. However, their survival and growth are often threatened by their limited access to critical resources like risk management instruments, insurance, savings, and credit, which can hamper their ability to scale and adapt to economic challenges [12],[13].

One of the major challenges that MSMEs face in the logistics sector, particularly in regions like Batam City, is the lack of efficient infrastructure and technology to streamline operations. The need for improved logistics solutions that are affordable and scalable is critical for MSMEs to remain competitive. In regions where resources are limited, MSMEs often struggle to find affordable solutions for inventory management, shipping, and overall supply chain optimization, which further hinders their potential for growth and sustainability. Addressing these challenges through digitalization and better logistics management is vital for the continued success of MSMEs in such areas.

2.2. Digital Transformation and Data Science in MSMEs

MSMEs are increasingly pressured to adopt digital technologies in order to compete in today's fast-evolving markets. Digitalization has become a driving force behind MSME growth, offering tools to improve business processes, increase operational efficiency, and reach global markets. The digital transformation involves not only adopting new technologies but also rethinking business models and strategies, which can be disruptive to traditional practices. As MSMEs embrace digital transformation, they stand to gain improved market access, customer engagement, and operational productivity, all of which are essential for growth in the digital age [14].

Several emerging technologies are playing a pivotal role in reshaping MSMEs. Artificial intelligence (AI), the Internet of Things (IoT), and big data analytics are key enablers of digital transformation. AI can automate tasks, enhance decision-making, and improve customer experiences, while IoT allows businesses to monitor and optimize their operations through interconnected devices. Big data analytics further supports MSMEs by offering insights into consumer behavior, market trends, and operational efficiency. These technologies are revolutionizing how MSMEs operate, enabling them to compete more effectively with larger enterprises in a globalized market [15].

While the potential benefits of digital transformation are significant, MSMEs often face several challenges in their adoption of new technologies. The main hurdles include high initial costs, lack of skilled personnel, and resistance to change within the organization. In the logistics sector, MSMEs are especially impacted by the lack of digital infrastructure and the challenge of integrating new technologies into existing processes. The complexities of adopting AI, IoT, and big data in logistics systems can overwhelm smaller enterprises that lack the resources and technical expertise needed for a smooth transition. Additionally, logistics and delivery operations are often fragmented and inefficient, which makes it even harder for MSMEs to capitalize on digital solutions [16].

Data science is emerging as a critical tool for MSMEs, particularly in the optimization of logistics processes. By leveraging predictive analytics, MSMEs can forecast demand, identify optimal shipping routes, and manage inventory more effectively. Predictive analytics, powered by big data, enables MSMEs to anticipate customer needs, adjust delivery schedules, and reduce operational costs. Route optimization algorithms, for instance, can minimize fuel consumption and improve delivery times, ultimately enhancing customer satisfaction and reducing logistics expenses. As MSMEs continue to integrate data science into their operations, they will be better positioned to optimize their supply chains and deliver products in a more efficient, cost-effective manne [17],[18].

2.3. Clustering and Its Applications in MSME Logistics

Clustering is a powerful technique used in data analysis, particularly in the logistics sector, where it can reveal valuable insights into customer behaviors, usage patterns, and service preferences. Several clustering methods have been developed to handle various types of data, including K-Means, hierarchical clustering, and DBSCAN, each offering unique benefits. K-Means is widely used due to its simplicity and efficiency. It works by partitioning data into K clusters based on similarity, with the goal of minimizing variance within each cluster. It has been extensively applied in customer segmentation, allowing businesses to group customers based on purchasing behavior, preferences, and other characteristics. Hierarchical Clustering builds a tree-like structure of clusters, where each data point starts in its own cluster, and clusters are progressively merged or split based on similarity. It is particularly useful when the number of clusters is not predefined, and the goal is to explore how clusters form at various levels of similarity. DBSCAN (Density-Based Spatial Clustering of Applications with Noise), unlike K-Means, which requires the number of clusters to be specified in advance, DBSCAN identifies clusters of varying shapes based on the density of points. This is particularly useful in logistics apps for identifying customer behaviors in spatially dispersed datasets, such as those derived from location data or user activity logs. These methods allow businesses in the logistics sector to better understand and predict customer needs, helping to improve service offerings and target specific segments effectively.

Clustering techniques are invaluable for analyzing customer behavior and usage patterns in logistics apps, enabling businesses to tailor their services more effectively. For example, K-Means clustering can be used to segment customers based on their frequency of use, preferred service types, and even geographical location. This segmentation allows logistics companies to customize their offerings, improving customer satisfaction and operational efficiency. Recent studies demonstrate the effectiveness of clustering in analyzing mobile app usage patterns. Priyanga and Kamal, for instance, employ hierarchical flexi-ensemble clustering to analyze mobile app usage, specifically in the logistics sector. Their research emphasizes the significance of clustering in understanding customer preferences, such as which logistics features customers use most frequently and how often they interact with the app. Similarly, Lee et al. used a combination of clustering and classification techniques to segment customers based on recency, frequency, and monetary value (RFM), providing insights that help businesses in targeted marketing and service improvements [19]. The integration of customer engagement metrics with clustering algorithms further enhances the understanding of usage patterns. Lin et al. found that high levels of customer engagement positively influence behavioral intentions, suggesting that businesses could benefit from personalized experiences, such as gamification, to retain customers and drive repeated usage [20]. This approach is critical for logistics companies, where retaining users is key to sustaining growth and building brand loyalty.

The SILCARE platform, which focuses on customer interactions and behaviors, can significantly benefit from behavioral clustering techniques. By leveraging clustering algorithms, businesses can categorize customers based on their purchasing habits, service usage, and satisfaction levels, leading to more effective marketing strategies and improved customer engagement. One of the foundational approaches for behavioral segmentation is the Recency, Frequency, and Monetary (RFM) model, which is often integrated with clustering algorithms to provide deeper insights into customer value. For instance, Qiasi et al. demonstrated how RFM-based clustering can identify customer loyalty and value, allowing businesses to tailor their offerings based on behavioral characteristics . Similarly, the RFMTS model, which includes a satisfaction score, further refines this approach, enabling businesses to segment customers more accurately and develop customized marketing strategies [21].

The K-Means algorithm, which has been widely applied in customer segmentation studies, proves particularly effective in the logistics context. Studies by Tabianan et al. illustrate how K-Means can be used to categorize customers based [22] on their purchasing and spending habits, thereby enabling businesses to gain valuable insights into their customer base. This method aligns with findings from Gao et al., who emphasize the importance of optimizing clustering techniques in big data environments, which is essential for accurate customer segmentation [23]. Advanced clustering techniques, such as density peak-based fuzzy clustering, have also shown promise in improving segmentation outcomes by capturing the complexities of customer behaviors. Nguyen's research highlights how such techniques can better represent the nuances of customer interactions, making them particularly useful for platforms like SILCARE, where understanding detailed customer preferences is crucial [24].

2.4. Mobile Technology and Android in MSME Logistics

Android technology plays a crucial role in the logistics operations of Micro, Small, and Medium Enterprises (MSMEs). Given that Android is the most widely used mobile operating system, it has become a central platform for the development of mobile applications that optimize logistics in small businesses. With over 70% of mobile devices globally running on Android, it is evident that this platform is a primary tool in the logistics sector, offering small enterprises an accessible and cost-effective means of streamlining their operations [25]. Android's open-source nature enables businesses to customize apps to meet specific logistical needs, providing them with tailored solutions that enhance efficiency and reduce operational cost [26], [27]. Mobile applications designed specifically for logistics in MSMEs have become essential tools for managing shipping and delivery processes. These apps integrate with various shipping carriers, allowing small businesses to track shipments in real-time, schedule deliveries, and manage inventory seamlessly. The simplicity and convenience of mobile logistics apps reduce the reliance on complex systems and allow businesses to provide better customer service, ultimately improving operational efficiency. Given the increasing reliance on smartphones, these apps are invaluable in helping MSMEs address logistical challenges without requiring substantial investment in expensive infrastructure .

Mobile technology has significantly impacted MSME business operations, particularly in the logistics and delivery sectors. Through mobile apps, businesses can improve customer experiences by providing real-time updates, tracking deliveries, and offering flexible delivery options. The integration of smartphones with logistics operations not only boosts customer satisfaction but also enhances the overall efficiency of business operations. As smartphones become increasingly advanced, the incorporation of features such as GPS for route optimization, data analytics for inventory management, and direct customer communication via mobile apps is transforming MSME logistics into a more agile and responsive syst. By adopting mobile technology, MSMEs can achieve higher productivity and foster stronger customer relationships, which are key drivers of business growth and sustainability. This shift in the logistics landscape is crucial for MSMEs looking to stay competitive in an increasingly digital world.

3. Methodology

3.1. System Usability Evaluation and Testing

System usability evaluation and testing is a critical phase to ensure that the developed system meets both technical and user-centric standards. This phase aims to validate the system's functionality, performance, and overall usability through systematic testing methods and user feedback mechanisms.

The initial step involves rigorous functional testing to ensure that all features and functionalities of the system work as intended. This includes validating processes such as user registration, login, product management, and order confirmation. Test scenarios are designed to simulate real-world usage conditions, focusing on verifying that the system behaves as expected under various inputs and interactions. Simultaneously, performance testing is conducted to evaluate the system’s responsiveness, speed, and scalability. This involves measuring load times, response times, and the system's ability to handle multiple concurrent users without degradation in performance. These metrics are crucial for determining the system's reliability in dynamic, high-demand environments. Performance testing also identifies bottlenecks, such as slow data retrieval or inefficient workflows, which can then be optimized to improve the overall user experience [28].

To assess usability, the System Usability Scale (SUS) is utilized as a quantitative measure of user satisfaction. Participants are asked to complete a series of predefined tasks within the system, such as registering, adding products, and confirming orders. Afterward, they respond to a 10-item SUS questionnaire designed to gauge various aspects of the system's usability, such as ease of use, intuitiveness, and perceived reliability. Each question is rated on a 5-point Likert scale, with responses contributing to a composite SUS score. The SUS test is conducted in two stages. Pre-Test Evaluation involves testing the initial version of the system to identify usability challenges. Lower SUS scores in this phase often highlight issues such as unclear workflows, complex navigation, or inconsistent interfaces. After incorporating feedback and implementing design improvements, a second SUS evaluation is conducted as Post-Test Evaluation. Higher scores in this phase reflect enhancements made to the system's usability and user satisfaction [29], [30].

Feedback from the functional, performance, and usability testing stages is used to guide iterative refinements to the system. Identified issues, such as interface inconsistencies or feature inefficiencies, are addressed through targeted updates. For example, if users struggle with product management tasks, additional tooltips or workflow simplifications may be implemented. These refinements are then re-evaluated to ensure that they effectively resolve the identified challenges. This systematic approach ensures that the system not only functions reliably but also delivers a seamless and satisfying user experience. By integrating SUS testing with functional and performance assessments, this phase provides a comprehensive evaluation of the system's effectiveness, usability, and readiness for deployment [31].

3.2. User Interaction Data Collection

The collection of user interaction data is essential for evaluating the real-world effectiveness and usability of the SILCARE system. Following the system’s deployment, interaction data was gathered from 100 SME users who performed key tasks such as registration, login, adding products, updating product details, and confirming orders. This data provides critical insights into how users engage with the platform and serves as a foundation for identifying areas of improvement [32].

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The analysis focused on several key user activities, with particular attention given to the time spent on each task. For example, the time required for registration and the login process was recorded to assess the efficiency with which users could access the system. Additionally, more complex tasks such as adding and updating products—critical functions for inventory management—were monitored. These tasks tend to be more time-consuming, so tracking the time spent on them revealed potential inefficiencies or challenges users faced [33].

The data also captured the time spent on simpler, yet essential tasks like deleting products and confirming orders. These tasks are integral to system functionality, and understanding the time required for them provided valuable insights into how users interacted with the system. By examining these time metrics, it became evident which actions took longer than expected and which were completed more efficiently.

This detailed dataset allowed for the identification of user behavior patterns and pain points within the system. For example, the extended time spent on tasks like adding and updating products highlighted potential areas for workflow optimization. These findings suggest the need for simplifying product management processes and improving guidance for users, particularly those who may be interacting with the system for the first time. Overall, the collected interaction data is a valuable resource for refining the system to better meet user needs and enhance overall user satisfaction .

3.3. User Clustering and Profiling

Exploratory Data Analysis (EDA) is performed on the collected user interaction data to gain a thorough understanding of the patterns and behaviors exhibited by SME users. EDA examines key variables, such as the time spent on registration, login, adding products, updating product details, and order confirmation. This phase helps identify trends, detect anomalies, and gain insights into user engagement, providing a foundation for more advanced techniques like clustering.

EDA begins by visualizing the distribution of time spent on each activity using tools such as histograms, box plots, and scatter plots. For example, the analysis might show that the time spent on registration and login is relatively consistent among users, while there may be greater variability in the time spent on tasks like adding products or updating product details. Box plots can reveal outliers—users who take significantly longer or shorter than average to complete certain tasks. These insights help identify areas for improvement in the system, such as potential complexity in the registration process or inefficiencies in the product management workflow [34].

Following the EDA phase, DBSCAN (Density-Based Spatial Clustering of Applications with Noise) is applied to group users based on their interaction patterns. The clustering algorithm uses the time spent on various tasks, identified during EDA, as features to detect groups of users with similar behaviors. The goal is to isolate users exhibiting atypical or erratic behavior while identifying those with consistent interaction patterns. Once the clusters are identified, each group is profiled based on its specific behaviors. Profiling these clusters provides valuable insights into the specific needs and pain points of each user group. It helps identify the root causes of inefficiencies or bottlenecks, such as unclear instructions or complex workflows for tasks like adding products. With these insights, targeted improvements can be made to the system's design. By leveraging the findings from EDA and clustering analysis, the system can be tailored to meet the diverse needs of its user base, ultimately enhancing user satisfaction and system usability [35].

3.4. Data Analysis and System Improvement

In this phase, the findings from the user interaction data and clustering analysis are thoroughly analyzed to guide system improvements. The insights gained from the time spent by users on various tasks, such as registration, login, product management, and order confirmation, serve as a foundation for understanding user behavior and identifying areas where the system can be optimized. Clustering analysis plays a key role in this process, as it groups users based on their interaction patterns, allowing for a more granular understanding of the challenges faced by different user segments.

For example, users who struggle with tasks like registration may require a simplified workflow or additional guidance. By examining the time spent on these tasks, it becomes clear whether the process is too complex or unclear. For these users, improvements such as streamlining the registration form, offering step-by-step instructions, or providing tooltips can significantly enhance the user experience. This targeted approach ensures that the system is adaptable to the needs of users who may have difficulty navigating certain workflows [36].

Similarly, users who are highly engaged in product management, spending substantial time on adding and updating products, may benefit from more advanced features or optimized workflows. These users might require capabilities such as bulk product editing, more intuitive interfaces for updating product details, or faster access to frequently used functions. Understanding the specific tasks that these users prioritize allows the system to be refined with features tailored to their needs, increasing efficiency and satisfaction.

Overall, the data analysis and clustering insights guide continuous system optimization. By addressing the specific pain points identified for each user group, the system can be iteratively improved to provide a more user-centric experience. Targeted changes, such as the addition of tutorials, tooltips, or redesigned workflows, help ensure that the system remains effective and intuitive for a wide range of users, enhancing overall usability and supporting long-term user engagement [37].

4. Results and Discussion

The purpose of this study was to develop a system that meets the needs of users by incorporating various features aimed at improving functionality and user experience. The research followed a structured methodology, starting with requirements gathering, progressing through system development, deployment, and user interaction, and concluding with clustering and profiling. Each phase contributed valuable insights that were used to refine the system. The aim of the Results & Discussion section is to present the findings from these phases and interpret them in relation to the system's effectiveness and user satisfaction. By analyzing the outcomes from each stage, we can assess how well the system meets its objectives and determine areas for future improvement.

4.1. System Usability Evaluation Results

The System Usability Evaluation aimed to assess the overall functionality and user satisfaction of the SILCARE system. A structured approach was adopted, incorporating a range of test scenarios designed to validate the core functionalities of the application. These tests, conducted using the Black Box Testing methodology, focused on evaluating the system's input-output behavior without considering the internal mechanics. The scenarios assessed various key features, as shown in table 1, ensuring that the system functions as expected and meets the users' needs.

Table 1. System Test List

Test Case	Description	Test Type
Registration (SME, Buyer, and Courier)	Register an account in the SILCARE application by entering a full name, telephone number, and a valid email address.	Black Box
Login (SME, Buyer, and Courier)	Test the login functionality using the email and password provided during the registration stage.	Black Box
Add SME Type, Bank, and Address	Add the business name, bank account details, and business address to the system.	Black Box
Add Product	Test the functionality of the "Add Product" button to add a new product.	Black Box
Product Updates	Test the functionality to update product information using the product menu.	Black Box
Delete Product	Test the functionality of the "Delete Product" button to remove a product from the system.	Black Box
Order Confirmation (for MSME)	Confirm orders placed by buyers using the "Order" button within the MSME menu.	Black Box

A detailed menu structure evaluation was performed, specifically targeting the different roles within the SILCARE platform, including MSMEs, Buyers, and Couriers. The tests focused on ensuring that critical functionalities—such as managing products, processing orders, handling customer data, and adjusting settings—performed seamlessly. Different actions (e.g., adding, changing, viewing, exporting, filtering, and saving) within these menus were tested to ensure that each button and feature functioned properly, as shown in table 2. Additionally, the Log Out function was thoroughly tested to ensure it worked smoothly across all user roles, guaranteeing a secure and intuitive experience.

Table 2. Menu Structure List

Role	Sub Menu	Test Description	Test Type
SME	Products	Test the button to ensure its function work properly.	Black Box
	Order	Test the button to ensure its function work properly.	Black Box
	Customer	Test the button to ensure its function work properly.	Black Box
	Settings	Test the button to ensure its function work properly.	Black Box
Buyer	Order	Test the button to ensure its function work properly.	Black Box
	Customer	Test the button to ensure its function work properly.	Black Box
	Settings	Test the button to ensure its function work properly.	Black Box
Courier	Take	Test the button to ensure its function work properly.	Black Box
	Reject	Test the button to ensure its function work properly.	Black Box

Finally, the System Evaluation for Users involves a System Usability Scale , a method used to measure the overall satisfaction of users with the application. This evaluation aims to determine whether the system satisfies the users' needs and how well it supports their tasks, providing valuable insights for further refinement. The System Usability Scale test was conducted with both a pre-test and a post-test to evaluate the usability of a system and the improvements made during the testing phase. The SUS questionnaire used for both tests is outlined in table 3, which consists of 10 questions assessing various aspects of system usability. These questions are designed to gauge user satisfaction with the system, ranging from ease of use to functionality and reliability. The respondents were asked to rate their agreement with each statement on a 5-point Likert scale, from Strongly Disagree (1) to Strongly Agree (5).

Table 3. SUS Questionnaire Items

No	Item Questionnaire	Sources
1	I will continue to use this system.	[38]
2	I find this system easy to use.	[38]
3	I feel the features in this system work as intended.	[38]
4	I believe others will quickly understand how to use this system.	[38]
5	I found it smooth to use this system without any issues.	[38]
6	I think this system is too difficult to use.	[38]
7	I need technical assistance to be able to use this system.	[38]
8	I see many inconsistencies in this system.	[38]
9	I feel this system is very difficult to explore.	[38]
10	I need time to get used to it before using this system.	[38]

In the pre-test, the respondents’ scores across the 10 questionnaire items varied, leading to an average SUS score of 74.5. The score ranges from a low of 65 to a high of 82.5, indicating a mixed level of satisfaction with the system prior to any modifications or adjustments. The items with lower ratings, such as Question 6 ("I found the system unnecessarily complex") and Question 7 ("I needed to learn a lot of things before I could get going"), suggest that users found the system somewhat difficult or cumbersome to use, which led to a moderate score in the B range on the SUS scale (74.5). According to the SUS Assessment Instrument, a B grade indicates that the system's usability is in the acceptable range but still leaves room for improvement.

In the post-test, after improvements were implemented, the average SUS score rose to 90.25, a significant increase from the pre-test. This score suggests that the modifications made to the system had a substantial positive impact on usability. The range of scores for individual respondents in the post-test was between 82.5 and 100, with most participants reporting high levels of satisfaction. For instance, respondents rated the system highly on questions such as Question 1 ("I think that I would like to use this system frequently") and Question 4 ("I found the system easy to use"), which are key indicators of user satisfaction. In the post-test, participants consistently gave higher ratings across the board, reflecting the improved ease of use and overall functionality. The post-test scores fall within the A grade range, indicating that the system is now perceived as excellent, with usability greatly enhanced. According to the SUS Assessment Instrument, this A grade suggests that the system is now highly rated by users and considered to be the best imaginable.

The comparison of the pre-test and post-test results demonstrates a clear improvement in the system's usability. While the pre-test score of 74.5 indicated that the system was functional but still needed refinement, the post-test score of 90.25 reflects a significant improvement in user satisfaction and ease of use. The shift from a B (acceptable) grade to an A (excellent) grade on the SUS scale aligns with the improvements made to the system. The positive shift in scores suggests that the modifications addressed key usability issues identified in the pre-test, such as complexity and the need for extensive learning. Overall, the results of the SUS test provide strong evidence that the system's usability has been greatly enhanced, with users now finding the system both user-friendly and highly functional.

4.2. User Interaction Data Collection Results

The SILCARE system was successfully deployed to the target users, including 100 users from SMEs who were provided with access to the platform. During the deployment, users interacted with the system to perform various tasks such as registering, logging in, adding products, updating products, and confirming orders. These interactions were tracked and analyzed to gather valuable insights into the user experience and engagement with the system. The system allowed them to engage in various tasks such as registering, logging in, adding products, updating products, and confirming orders. During the initial deployment phase, there were some challenges related to user registration and login, with a small number of users encountering difficulties in entering the correct data during registration or facing login errors due to incorrect credentials. These issues were quickly addressed with minor system adjustments and clearer user instructions, improving the overall deployment experience.

The user interaction data collected provided valuable insights into how users engaged with the system, as summarized in table 4. On average, users spent approximately 7.11 minutes on registration, with a minimum of 3 minutes and a maximum of 10 minutes. This indicates that while most users were able to complete the registration process relatively quickly, some required additional time, possibly due to challenges in entering the required information. The time spent on login was slightly shorter, averaging 4.44 minutes. However, this activity had a wider distribution, with some users taking as little as 1 minute, while others spent up to 8 minutes, likely due to password retrieval or errors in entering credentials.

Table 4. Statistic Summary of User Interaction Data

Task	Count	Mean	Std Dev	Min	25%	50%	75%	Max
Registration	100	7.11	2.57	3	5	8	10	10
Login	100	4.44	2.31	1	3	3	8	8
Add SME Type, Bank, and Address	100	8.58	2.57	5	8	8	9	15
Add Product	100	8.91	2.71	5	6	8	12	15
Product Updates	100	8.59	1.91	3	8	8.5	9	12

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Delete Product	100	4.57	2.35	2	3	3	8	8
Order Confirmation	100	5.15	2.06	2	4	5	8	8

For the task of adding SME type, bank, and address information, users spent an average of 8.58 minutes. This task showed more variation, with the time spent ranging from 5 minutes to 15 minutes. This variability could be attributed to the complexity of the information required and users' familiarity with the system. Similarly, the process of adding a product took an average of 8.91 minutes, with a range from 5 to 15 minutes. This activity, which is crucial for populating the system with products, had a relatively consistent time distribution, with most users completing it efficiently.

Updating product information required an average of 8.59 minutes, and the time ranged from 3 to 12 minutes. Like adding products, this task involved a more consistent amount of time, though some users took longer to review and update the product details. Deleting products, on the other hand, was a faster activity, with an average time of 4.57 minutes. The time spent on this task ranged from 2 to 8 minutes, suggesting that users found it straightforward to delete items, with only minor variation across users. Lastly, confirming orders took an average of 5.15 minutes, with most users completing the task in a range from 2 to 8 minutes. This activity had the lowest variability, indicating that users were able to confirm orders fairly quickly once they understood the process.

For SME users, the data reveals that the registration process took an average of 7.5 minutes, which indicates that while the majority of users were able to complete the registration flow smoothly, there was still some variability in the time spent, possibly due to differences in data entry. Adding products, the most critical function for SMEs, took an average of 9.5 minutes per product, highlighting the level of engagement in populating their inventory. SMEs also spent an average of 9 minutes updating product details, reflecting the importance they place on maintaining accurate product information. In terms of order confirmation, SMEs spent around 5.5 minutes completing the task, which was relatively quick compared to the more data-intensive activities like adding and updating products.

The user data highlighted several engagement patterns and insights. Activities that involved more detailed inputs, such as adding and updating products, as well as confirming orders, were among the most time-consuming tasks. This is likely due to the need for attention to detail in ensuring the accuracy of product information and order fulfillment. Conversely, activities that required fewer inputs, such as logging in or deleting products, were completed more quickly and with less variation in time. The variability observed in tasks such as registration, login, and adding products suggests that some users may have struggled with these processes, potentially due to unfamiliarity with the system or confusion over the required inputs. This indicates that there may be opportunities for system improvements, such as enhanced user onboarding or clearer guidance to streamline these tasks and reduce the time spent. Overall, the data provided useful feedback for enhancing the user experience and increasing the system's efficiency moving forward.

4.3. User Clustering and Profiling Results

The user clustering process utilized the Density-Based Spatial Clustering of Applications with Noise algorithm to group users based on their interaction data, including time spent on various system features such as registration, login, product management, and order confirmation. The clustering analysis identified four distinct user groups, including one noise cluster labeled as `-1`, which captured users with irregular behavior patterns or outliers. The silhouette score for the clustering was calculated at 0.55, indicating moderately well-defined clusters. Each cluster represents a unique behavior pattern, reflecting the varying ways users engage with the SILCARE system, as shown in table 5.

Table 5. Task Completion Time of Each Cluster

DBSCAN Cluster	Task Completion Time (Minutes)						
	Registration	Login	Add SME Type, Bank, and Address	Add Product	Product Updates	Delete Product	Order Confirmation
-1	6.57	3.51	10.27	9.92	7.7	3.86	3.97
0	8	8	8	7.96	8	8	8

1	10	3	9	6.05	9	3	4
2	3	3	5	12	11	3	5

Cluster -1 consists of 37 users whose interaction data deviated from the norm, potentially representing irregular usage patterns. These users spent an average of 6.57 minutes on registration, 3.51 minutes on login, and 10.27 minutes on adding SME type, bank, and address information. They also engaged moderately with adding products (9.92 minutes) and updating products (7.70 minutes) but spent less time on order confirmation (3.97 minutes) and deleting products (3.86 minutes). This group could represent users who are experimenting with the system but are not fully committed to its functionalities. Cluster 0 includes 25 users who exhibit balanced engagement across all activities. These users spent 8 minutes on every task, including registration, login, and product management. This uniformity suggests that these users are systematic and consistent in their use of the system. They may represent SMEs that fully understand and utilize the system as intended.

Cluster 1 is composed of 22 users who focused heavily on the initial stages of the system, spending an average of 10 minutes on registration, 3 minutes on login, and 9 minutes on adding SME type, bank, and address information. However, their time spent on adding products was relatively low (6.05 minutes), indicating less emphasis on inventory management. This group might include newer users or those who are still becoming familiar with the system's full functionality. Cluster 2 encompasses 16 users who heavily engaged in product-related tasks, spending 12 minutes on adding products and 11 minutes on updating them. These users allocated less time to other activities, such as registration (3 minutes), login (3 minutes), and entering SME type, bank, and address information (5 minutes). This cluster likely represents power users who focus primarily on managing their inventory within the system.

Each identified cluster reflects specific user behaviors and needs. For example, Cluster -1 represents irregular users or potential outliers who may benefit from enhanced onboarding or clearer guidance. In contrast, Cluster 0 represents ideal users who utilize the system as intended, highlighting its usability for SMEs with systematic workflows. Cluster 1 indicates users who are likely in the onboarding phase or struggling with advanced functionalities, suggesting a need for additional support during registration and initial setup. Lastly, Cluster 2 represents highly engaged users focused on inventory management, emphasizing the importance of optimizing product-related features for this group.

The clustering analysis provides actionable insights for future system improvements. For instance, simplifying registration and login workflows can address the challenges faced by Cluster 1 users. Enhancing product management features, such as adding shortcuts or templates, could improve the experience for Cluster 2 users. Moreover, providing targeted tutorials or personalized interfaces for outlier users in Cluster -1 could help reduce irregular usage patterns and encourage consistent engagement. By understanding and addressing the unique needs of each cluster, the SILCARE system can continue to evolve into a more user-centric and effective platform.

4.4. Discussion of Findings

The user interaction data provides significant insights into how different users engage with the system. The key finding from this analysis is the variation in the time users spend on tasks. Simple tasks, such as registration and login, are completed quickly, suggesting that the interface is intuitive and the workflows are well-designed. These tasks appear to be straightforward and user-friendly, likely due to the clarity of the system's interface. On the other hand, tasks related to product management—such as adding or updating product details—are more time-consuming. This indicates that these actions are more complex and involve multiple steps, which may not be as intuitive to all users. The fact that some users struggled with these tasks suggests that the interface for managing products might not be as user-friendly as needed, or it could benefit from more detailed instructions or support. This pattern emphasizes the need for workflow refinement. Tasks involving complex processes, such as updating product details, should be simplified. Features like tooltips or tutorials could help users navigate these tasks more efficiently. This insight aligns with existing research that stresses the importance of intuitive design in improving user experience, especially for complex operations.

The clustering analysis reveals distinct groups of users with varying levels of engagement and interaction with the system. By understanding the unique characteristics of each cluster, we can tailor the system to meet the diverse needs of its users more effectively. Cluster -1 consists of users who tend to spend more time on tasks such as adding SME type, entering bank details, and updating products. These users may be less familiar with the system or find certain processes more challenging. Their struggles suggest that these tasks are more complex for them and may require additional support. To improve the experience for this cluster, the system can benefit from simplified workflows, more intuitive design, and the introduction of step-by-step guides or tutorials. Providing additional guidance, such as tooltips or interactive help, could significantly reduce the time they spend on these tasks and help them navigate the platform with greater ease. Cluster 0 shows a more balanced and efficient interaction across different tasks, indicating that users in this group are generally comfortable with the system. These users likely have prior experience with similar platforms and are able to complete tasks with relative ease. To cater to this cluster, the system could offer more advanced features without the risk of overwhelming them. Power users in Cluster 0 may benefit from customizations or access to more complex options, enabling them to complete tasks more efficiently and access additional functionalities that are tailored to their experience level.

Cluster 1 represents a group of users who engage efficiently with most tasks but may still experience some delays or challenges with more intricate processes like product management and SME entry. While their performance is generally good, some processes still seem slightly more time-consuming or difficult to navigate. Users in this cluster could benefit from minor improvements to the system's design, such as enhanced task clarity or additional context-based support. For instance, better explanations of certain steps or automatic suggestions could guide them through the process with more ease and speed. Users in Cluster 2 display the most efficient interactions across all tasks, spending relatively little time on registration, product updates, or other actions. This suggests that they are highly familiar with the system and perhaps have considerable experience with similar platforms. For this group, the system could prioritize speed and advanced functionality, offering shortcuts or customizable workflows to improve productivity. Additionally, providing fewer prompts or simplifying unnecessary steps could improve the overall experience for these proficient users, ensuring that their advanced needs are met without friction.

By identifying the unique behaviors and needs of these user clusters, we can make data-driven improvements to the system. For Cluster -1, simplifying workflows, offering more tutorials, and providing real-time support will help reduce the friction and time spent on complex tasks. Cluster 0 will benefit from providing advanced features and customization options without overwhelming them with unnecessary complexities. Cluster 1 will likely find further improvements in clarity and guidance helpful to streamline their experience, especially on slightly more complicated tasks. Cluster 2 will appreciate features that cater to their speed and proficiency, enabling them to work more efficiently and with less guidance. This segmentation approach allows for a more personalized user experience, improving overall satisfaction and system effectiveness. Tailoring the system to accommodate users at different levels of proficiency ensures that the platform remains accessible and efficient for all.

The insights drawn from the user interaction data and clustering analysis provide a solid foundation for improving the system's design and features. Several strategies can be employed to enhance user experience. For users in Cluster -1, simplifying the registration process could help reduce the time spent on initial tasks. By making the registration flow clearer and less cumbersome, we can improve the first interaction with the system. Offering contextual help in the form of tutorials or interactive tooltips could significantly benefit users struggling with more complex tasks. Tasks such as adding and updating product details could be accompanied by on-screen guidance that helps users understand the steps involved and the information needed. Implementing step-by-step guides for tasks like product management could reduce confusion and frustration, especially for novice users. A clearer navigation flow would make these tasks feel less overwhelming and more intuitive. The user interface could be adjusted to better accommodate different user needs. For example, users in Cluster -1 may benefit from a simplified interface, while users in Cluster 0 could have access to more advanced settings and features without adding complexity to the system's overall design. By focusing on these key areas, the system can be better tailored to suit a wider range of users, ensuring that both novice and expert users have a positive and efficient experience.

The system shows strong potential in meeting user needs but also has room for improvement in terms of usability. The analysis indicates that while some users find the system intuitive and satisfying, others encounter difficulties that impact their experience, particularly with complex tasks. Feedback from various testing methods, including SUS scores (System Usability Scale) and direct user responses, reveals a mixed reception. Some users express satisfaction with the system's simplicity, while others struggle with more involved tasks. These findings suggest that the system's overall effectiveness could be enhanced by focusing on making complex tasks more intuitive, reducing the time spent on these tasks, and offering clearer guidance to users who may not be as familiar with the platform. In conclusion, the system's usability can be greatly improved by continuing to refine workflows, incorporating helpful tools like tutorials and guides, and ensuring that the system evolves to meet the diverse needs of its user base. The importance of continuous user testing and refinement cannot be overstated to ensure that the system becomes increasingly user-friendly over time.

5. Conclusion

The analysis of user interaction data from the SILCARE system reveals significant insights into how different user clusters engage with the platform. The findings highlight that users in Cluster -1, who struggle with more complex tasks like adding SME details and product management, would benefit from simplified workflows and additional support. Meanwhile, Cluster 0, characterized by users who navigate the system with ease, indicates that familiarity with similar platforms plays a key role in user efficiency. These insights underscore the importance of a tailored user experience, where workflows are optimized to meet the specific needs of various user groups, thereby enhancing overall satisfaction. Despite the promising results, several limitations exist in the study. The user sample size may not fully represent the diverse range of MSMEs using the SILCARE system, which could affect the generalizability of the findings. Additionally, while the data provides valuable insights into user behavior, it may not fully capture the context behind certain interactions, such as environmental or organizational factors that influence user experience. These limitations point to the need for a broader, more diverse sample in future studies to gain a more comprehensive understanding of user needs. The next steps for system development should focus on addressing the pain points identified in the analysis, particularly for Cluster -1 users. This could include incorporating contextual help, tutorials, and more intuitive workflows for complex tasks. Additionally, gathering more user feedback through surveys and continuous testing will be essential to refine the system further and ensure that it evolves to meet the needs of its users. Iterative development, informed by data-driven insights, will help create a system that can adapt to the diverse and dynamic nature of MSME shipping. In conclusion, the SILCARE system holds significant potential to revolutionize MSME shipping by offering an intuitive, data-driven solution that can improve user satisfaction and efficiency. By addressing user challenges and refining the system based on user feedback, SILCARE can become a more robust platform that caters to the unique needs of MSMEs. Future improvements, such as enhanced features for power users and more streamlined processes for beginners, will further solidify the system's impact on the MSME shipping industry, helping to drive productivity and growth in this vital sector.

6. Declarations

6.1. Author Contributions

Conceptualization: R.D.P., M.A.B., L.H., T.S., H.F., N.S., and T.A.S.; Methodology: R.D.P., L.H., M.A.B., and T.S.; Software: R.D.P., L.H., H.F., and N.S.; Validation: R.D.P., N.S., and T.A.S.; Formal Analysis: R.D.P., N.S., and T.A.S.; Investigation: R.D.P., T.S., M.A.B., and L.H.; Resources: N.S.; Data Curation: R.D.P., N.S., and T.S.; Writing Original Draft Preparation: R.D.P., M.A.B., L.H., T.S., H.F., N.S., and T.A.S.; Writing Review and Editing: R.D.P., M.A.B., L.H., and T.S.; Visualization: H.F., N.S., and T.A.S. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding.

6.3. Funding

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6.4. Institutional Review Board Statement

This study did not require approval from an Institutional Review Board, as it does not involve human or animal subjects.

6.5. Informed Consent Statement

This study did not involve human participants requiring informed consent.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this study.

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