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Web-Based Laundry Customer Segmentation Using Agglomerative Hierarchical Clustering

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Abstrak

Data transaksi pelanggan pada bisnis laundry menawarkan wawasan perilaku yang berharga, namun seringkali hanya dimanfaatkan untuk pencatatan operasional. Penelitian ini mengembangkan fitur segmentasi pelanggan berbasis web untuk Rayhan Laundry menggunakan Agglomerative Hierarchical Clustering (AHC). Metodologi ini mengagregasi 13.904 transaksi historis menjadi 1.528 profil pelanggan, dengan total berat laundry dan frekuensi transaksi sebagai fitur perilaku yang telah distandardisasi. Dikonfigurasi dengan jarak Euclidean dan Ward linkage, model AHC mencapai Silhouette Score sebesar 0,753, mengidentifikasi tiga segmen: 36 pelanggan bervolume tinggi, 209 pelanggan reguler, dan 1.283 pelanggan sporadis. Output analitik ini diintegrasikan ke dalam aplikasi web berbasis Laravel. Evaluasi sistem mengonfirmasi fungsionalitas yang kuat, dengan seluruh sepuluh skenario uji black-box berhasil. Selain itu, penilaian kegunaan melalui System Usability Scale (SUS) menghasilkan skor rata-rata 82,75, mengklasifikasikan antarmuka sebagai "Excellent." Penelitian ini mendemonstrasikan kelayakan teknis dan kegunaan tinggi dalam mengoperasionalkan segmentasi pelanggan berbasis transaksi.

Kata kunci*—Agglomerative Hiearchical Clustering, Segmentasi Pelanggan, Aplikasi Laundry, Blackbox Testing, System Usability Scale*

Abstract

Customer transaction data in laundry businesses offer valuable behavioral insights but are frequently underutilized for mere operational record-keeping. This study develops a web-based customer segmentation feature for Rayhan Laundry utilizing Agglomerative Hierarchical Clustering (AHC). The methodology aggregated 13,904 historical transactions into 1,528 customer profiles, utilizing total laundry weight and transaction frequency as standardized behavioral features. Configured with Euclidean distance and Ward linkage, the AHC model achieved a Silhouette Score of 0.753, identifying three distinct segments: 36 high-volume, 209 regular, and 1,283 sporadic customers. These analytical outputs were seamlessly integrated into a Laravel-based web application. System evaluation confirmed robust functionality, with all ten black-box test scenarios passing successfully. Furthermore, usability assessments via the System Usability Scale (SUS) yielded an average score of 82.75, classifying the interface as "Excellent." Ultimately, this research demonstrates the technical feasibility and high usability of operationalizing transaction-based customer segmentation within a web application, providing a practical tool for targeted service planning.

Keywords*—Agglomerative Hierarchical Clustering, Customer Segmentation, Laundry Application, Blackbox Testing, System Usability Scale*

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1. INTRODUCTION

Service-sector small and medium-sized enterprises (SMEs) continuously generate transactional data during their daily operations. In the context of laundry services, these records typically encompass customer demographics, transaction dates, and laundry weights. While such data offer insights into customer activity, they are frequently underutilized, often restricted to basic operational record-keeping rather than being leveraged to uncover underlying behavioral patterns. Customer segmentation presents a strategic approach to transforming these raw transactional records into interpretable cohorts, thereby facilitating more informed service planning and enhanced customer relationship management (CRM).

Sustaining customer loyalty is critical for the long-term viability of service-oriented enterprises. Within the laundry service domain, prior studies have extensively explored the interplay among service quality, customer trust, satisfaction, and loyalty [1]. Comprehending behavioral heterogeneity can augment these service-centric factors by enabling business owners to identify and cater to varying levels of service utilization. For instance, high-frequency patrons may necessitate distinct retention strategies compared to occasional users. Crucially, such distinctions must be empirically derived from observed transactional patterns rather than relying on subjective assumptions regarding customer preferences.

Customer segmentation categorizes individuals based on shared characteristics, with transaction-based approaches frequently employing clustering algorithms to isolate cohorts exhibiting similar purchasing or service-usage behaviors. Existing literature has demonstrated the efficacy of combining Recency, Frequency, and Monetary (RFM) analysis with K-Means clustering to optimize CRM and marketing strategies [2], [3], while other investigations have utilized K-Means specifically for sales transaction segmentation [4]. Although these methodologies underscore the utility of transaction-derived features, the variables and clustering protocols inherent to general retail contexts cannot be directly extrapolated to laundry services. In the latter domain, transaction frequency and the cumulative weight of processed laundry serve as the most direct and relevant metrics of service utilization.

Previous studies have compared K-Means and hierarchical clustering for customer and retail segmentation, demonstrating the relevance of evaluating clustering methods in relation to their respective datasets and evaluation criteria [5], [6], [7], [8]. While comparative studies offer frameworks for evaluating diverse clustering algorithms, recent research has also explored advanced clustering methods in e-commerce, integrating feature transformation with various algorithmic approaches [9], [10]. For this study, Agglomerative Hierarchical Clustering (AHC) is particularly pertinent, as it constructs a hierarchical tree of clusters via successive merging, a structure that can be visually and analytically interpreted through a dendrogram. By employing Ward linkage, the algorithm minimizes the variance within clusters at each merging step. When coupled with Euclidean distance and standardized numerical features, AHC effectively groups customers based on transactional similarities. Nevertheless, the empirical suitability of AHC for this specific dataset must be rigorously validated through cluster evaluation metrics rather than presumed solely from its theoretical properties.

Despite these methodological advancements, a practical challenge persists for small-scale laundry enterprises, transaction-based segmentation must yield not only interpretable clusters but also be seamlessly integrated into the business's existing information systems. While clustering literature provides robust theoretical foundations, the analytical outputs must be operationalized into accessible formats for routine managerial use. Consequently, the research problem for Rayhan Laundry is twofold, first, to effectively segment customers based on observable transactional behaviors, and second, to embed these segments into a web-based application that facilitates practical data inspection. This study addresses this gap by applying AHC to two

primary behavioral variables, cumulative laundry weight and transaction frequency, and subsequently embedding the resulting segmentation model into the Rayhan Laundry web application.

The primary objective of this study is to develop and evaluate a web-based customer segmentation module for Rayhan Laundry utilizing AHC. Historical transaction records are preprocessed and aggregated at the individual customer level to compute total laundry weight and transaction frequency. Following feature standardization, the clustering structure is assessed using the Silhouette Score. The derived customer cohorts are subsequently classified into high-volume, regular, and sporadic categories based on their behavioral profiles. These segmentation outcomes are then integrated into a Laravel-based web application, equipping administrators with functionalities to view, search, filter, paginate, and export segmented customer data. The functional integrity of the system is verified through black-box testing, while its perceived usability is quantified utilizing the System Usability Scale (SUS) [11].

This study makes three primary contributions to the field. First, it investigates the application of AHC for customer segmentation within the laundry service sector, specifically utilizing total laundry weight and transaction frequency as core behavioral features. Second, it operationalizes the derived customer cohorts within the Rayhan Laundry web application, transitioning the segmentation output from an isolated, offline analytical exercise into an accessible, application-level managerial tool. Third, it conducts a comprehensive evaluation of both the clustering efficacy and the developed software feature using the Silhouette Score, black-box testing, and SUS, thereby addressing cluster validity, functional correctness, and user-centric usability, respectively. It is important to note that this study does not directly quantify the subsequent impact on customer retention, revenue generation, or promotional efficacy, these business outcomes are delineated as avenues for future research.

2. METHODS

2.1. Research Design and Workflow

This study adopts an applied research design that synthesizes customer behavior analysis with web application development. The methodological framework comprises six sequential phases: data acquisition, data preprocessing, customer-level aggregation, clustering and evaluation, web application integration, and system evaluation. This workflow was systematically designed to transform raw historical laundry transaction records into actionable customer segments, seamlessly accessible through the Rayhan Laundry web application. The comprehensive workflow of the proposed methodologsy is illustrated in Figure 1.

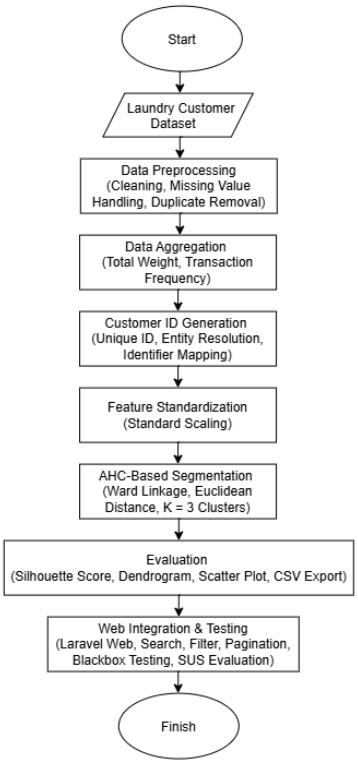


Figure 1 Research workflow

Initially, historical transaction data were sourced from Rayhan Laundry and prepared for analysis by standardizing customer identifiers and validating data quality. Subsequently, transaction records were aggregated at the individual customer level to compute total laundry weight and transaction frequency. Following feature standardization, Agglomerative Hierarchical Clustering (AHC) was applied. The resultant clusters were evaluated using the Silhouette Score and visually inspected via a dendrogram and a scatter plot. Finally, the segmentation outputs were integrated into a Laravel-based web application and rigorously evaluated through black-box testing and the System Usability Scale (SUS).

2.2. Dataset and Feature Extraction

The primary dataset comprises 13,904 historical transaction records sourced from Rayhan Laundry. Each record encapsulates customer identification data, customer name, transaction timestamp, and laundry weight. Prior to clustering, these transactional records were aggregated to generate 1,528 distinct customer profiles.

Two quantitative variables were engineered to characterize customer behavior. The first, Total Laundry Weight, represents the cumulative volume of laundry processed for a specific customer over the observation period, calculated by summing individual transaction weights. The second, Transaction Frequency, denotes the total count of transactions associated with each customer, serving as a proxy for service utilization intensity. These variables were selected because they capture complementary dimensions of customer behavior, cumulative service volume and utilization frequency. Consequently, the resulting customer-level dataset consists of 1,528 observations, each defined by these two input features.

2.3. Data Preprocessing and Identifier Harmonization

Rigorous data preprocessing was executed to standardize customer identifiers and consolidate transaction records into consistent customer-level observations. Customer identifiers were harmonized utilizing a systematic generation protocol, records with valid phone numbers were assigned an ‘A-series’ identifier derived from the last four digits, supplemented by a

sequential prefix to resolve duplicates. Conversely, records lacking usable contact information were allocated 'B-series' identifiers based on unique customer names, adhering to a predefined fallback mechanism.

Following identifier harmonization, transactions were aggregated by the assigned customer ID. For each customer, the cumulative laundry weight was computed by summing individual transaction weights, while transaction frequency was derived by counting the associated records. This procedure successfully transformed the transaction-level dataset into a customer-level feature matrix comprising Total Laundry Weight and Transaction Frequency. It is important to note that because identifier harmonization dictates transaction grouping, the resulting segments must be interpreted in the context of the source data's identifier availability.

2.4. Cluster Implementation and Evalution

The clustering analysis was implemented in Python utilizing the Agglomerative Hierarchical Clustering (AHC) algorithm. Prior to model execution, the two input features were normalized using StandardScaler. This standardization step was critical to ensure comparability, as total laundry weight and transaction frequency exhibit disparate numerical magnitudes. The AHC model was configured with Euclidean distance metrics and Ward linkage, a combination selected to minimize the within-cluster sum of squares during successive merges, thereby grouping customers with analogous behavioral patterns.

To yield operationally actionable segments for the Rayhan Laundry application, the number of clusters was predetermined at three ($k = 3$). These clusters were subsequently labeled as high-volume, regular, and sporadic based on their empirical behavioral profiles. The hierarchical merging structure was validated via a dendrogram, while a scatter plot was employed to visualize the spatial distribution of customer profiles within the standardized feature space. The selection of three clusters reflects the specific operational configuration of this study and should not be construed as a universal optimum for all laundry datasets.

2.5. System Design and Web Application Integration

The resultant clustering output was exported in Comma-Separated Values (CSV) format and seamlessly integrated into the Rayhan Laundry web application, which was architected using the Laravel framework. The implemented module presents the segmentation outcomes within a comprehensive tabular interface, displaying customer identification, total laundry weight, transaction frequency, cluster assignment, and the corresponding behavioral category.

To facilitate intuitive data interaction, the module incorporates several core functionalities: a search mechanism for targeted record retrieval, category-based filtering, pagination for optimized data rendering, and data export capabilities for external reporting. Furthermore, a regeneration function was embedded to allow administrators to re-execute the clustering workflow directly from the application interface. This integration transitions the analytical output from a static, offline process into a dynamic, application-level managerial utility.

2.6. System Testing and Usability Assessment

The developed segmentation module underwent rigorous evaluation encompassing both functional testing and usability assessment. Functional validation was conducted utilizing a black-box testing methodology, which assesses system behavior by comparing actual outputs against expected results without inspecting the underlying source code [12], [13]. Test cases were designed to cover all primary functionalities, including cluster generation, result rendering, category filtering, search operations, pagination, data export, and workflow regeneration. Each test case was systematically evaluated and documented as either passed or failed.

Concurrently, perceived usability was quantified using the System Usability Scale (SUS) [11]. The evaluation involved 10 respondents who interacted with the developed feature and completed the standardized ten-item SUS questionnaire, rated on a five-point Likert scale. SUS scores were computed following the established scoring protocol, for positively phrased items,

the score contribution was calculated by subtracting one from the user's response, for negatively phrased items, the response value was subtracted from five. The aggregated contributions were then multiplied by 2.5 to yield a normalized score ranging from 0 to 100 per respondent. The final SUS metric was derived by calculating the mean of these individual scores. It is pertinent to note that while black-box testing verifies functional conformity and SUS measures perceived usability, these metrics do not directly quantify the segmentation's impact on business performance indicators such as revenue growth or customer retention.

3. RESULTS AND DISCUSSION

3.1. Data Preprocessing and Aggregation Results

The initial dataset comprised 13,904 raw laundry transaction records extracted from Rayhan Laundry. Each entry encapsulated customer identification data, customer name, transaction timestamp, and laundry weight. Following the preprocessing and aggregation protocols detailed in Section 2, these transactional records were consolidated into 1,528 distinct customer profiles. For each profile, two behavioral metrics were engineered, Total Laundry Weight (the cumulative weight of processed laundry) and Transaction Frequency (the total count of recorded transactions). This aggregation shifted the analytical focus from isolated transaction events to holistic customer service utilization, enabling the grouping of customers based on behavioral similarities. The resulting 1,528-profile feature matrix served as the foundational input for the subsequent AHC analysis.

3.2. Clustering Results and Customer Behavioral Profiles

The standardized customer-level dataset was subjected to Agglomerative Hierarchical Clustering (AHC) utilizing Ward linkage and Euclidean distance metrics. To mitigate scale disparities, input features were normalized via StandardScaler prior to model execution. The algorithm was configured to partition the data into three distinct clusters, yielding the behavioral profiles detailed in Table 1.

Table 1 Customer segmentation results

Cluster	Category	Customers	Percentage	Average Total Weight (kg)	Average Transaction Frequency
0	High-Volume Customers	36	2.35%	481.28	92.89
1	Regular Customers	209	13.68%	134.00	27.86
2	Sporadic Customers	1,283	83.97%	14.49	3.69
Total		1,528			

Cluster 0, designated as High-volume customers, encompasses 36 individuals (2.35% of the cohort). This segment exhibits a substantial average total laundry weight of 481.28 kg and an average transaction frequency of 92.89. These metrics signify intensive service utilization, positioning this cohort as a primary target for premium retention strategies and tailored service arrangements.

Cluster 1, classified as Regular customers, comprises 209 individuals (13.68%). With an average weight of 134.00 kg and a frequency of 27.86, this group demonstrates moderate service engagement, bridging the gap between the most active patrons and occasional users.

Cluster 2, representing Sporadic customers, constitutes the vast majority of the dataset (1,283 customers, 83.97%). Characterized by a low average weight (14.49 kg) and frequency (3.69), this segment reflects minimal cumulative engagement. While these customers may be targeted for reactivation campaigns, low transaction frequency does not inherently equate to dissatisfaction or imminent churn.

The pronounced class imbalance, with the sporadic segment dominating the distribution, is a critical empirical finding rather than a methodological flaw. It accurately reflects the natural consumption patterns within this specific dataset. Consequently, these segments should be interpreted as descriptive behavioral groupings rather than uniformly distributed or strictly hierarchical value tiers.

3.3. Cluster Evaluation and Visualization

The clustering structure was evaluated using the Silhouette Score. This metric compares the similarity of each observation to its assigned cluster with its dissimilarity to other clusters. The score ranges from -1 to 1, with higher positive values generally indicating that observations are more closely associated with their assigned clusters than with neighboring clusters [14].

The AHC model produced a Silhouette Score of 0.7525, reported as 0.753 after rounding. This result indicates favorable separation and cohesion under the selected clustering configuration. However, the score should be interpreted together with the cluster distribution, feature summaries, and visualizations rather than as conclusive evidence that the segmentation is optimal for all business purposes.

A dendrogram was generated to examine the hierarchical merging structure of the customer profiles, as illustrated in Figure 2. The dendrogram provides a visual representation of the sequence in which observations and clusters are merged at increasing linkage distances. The merging structure can inform the interpretation of possible cluster divisions, however, selecting three clusters should be understood as the configuration adopted in this study, rather than as a universally optimal number established by the dendrogram alone.

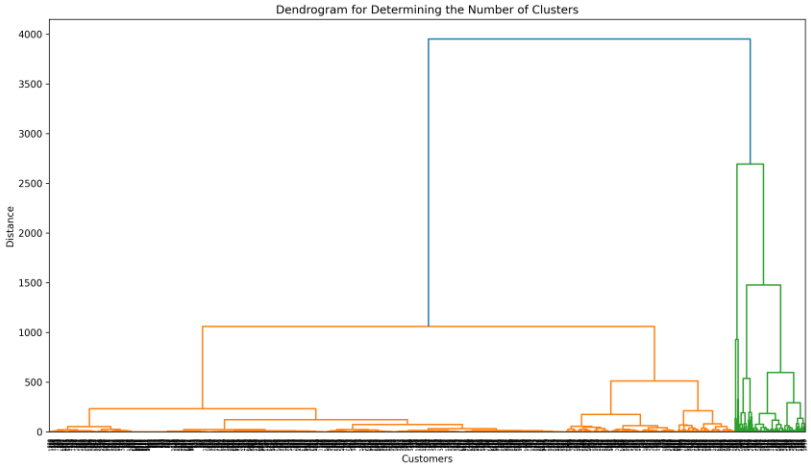


Figure 2 Dendrogram illustrating the hierarchical merging structure of customer data

Figure 3 presents a scatter plot of the customer profiles based on Total Laundry Weight and Transaction Frequency. The visualization illustrates the distribution of customers across the two behavioral dimensions and provides a complementary view of the segment assignments. Customers in the high-volume segment exhibit comparatively high values on these features, while sporadic customers are concentrated among profiles with lower weight and transaction frequency. Regular customers occupy an intermediate behavioral range.

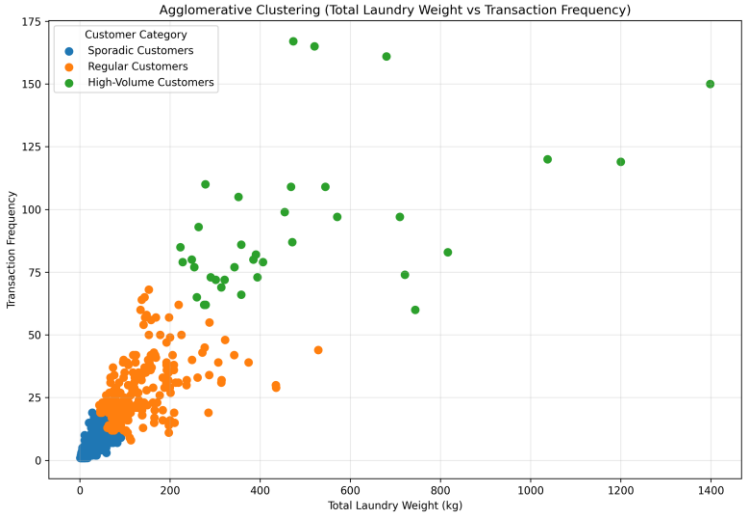


Figure 3 Spatial distribution and scatter plot of the customer segmentation results

Taken together, the Silhouette Score, cluster summaries, dendrogram, and scatter plot provide complementary evidence for interpreting the resulting segmentation. The evaluation supports the use of the model configuration for the analyzed dataset, while further work involving alternative cluster counts, clustering algorithms, or validation across different observation periods would be necessary to establish the robustness of the segmentation.

3.4. System Integration and User Interface Deployment

The clustering results were integrated into the Rayhan Laundry web application developed using the Laravel framework. As shown in Figure 4, the segmentation dashboard presents customer records together with their total laundry weight, transaction frequency, cluster assignment, and corresponding behavioral category. This interface allows users to examine the analytical output within the application rather than relying exclusively on a separate analytical environment.

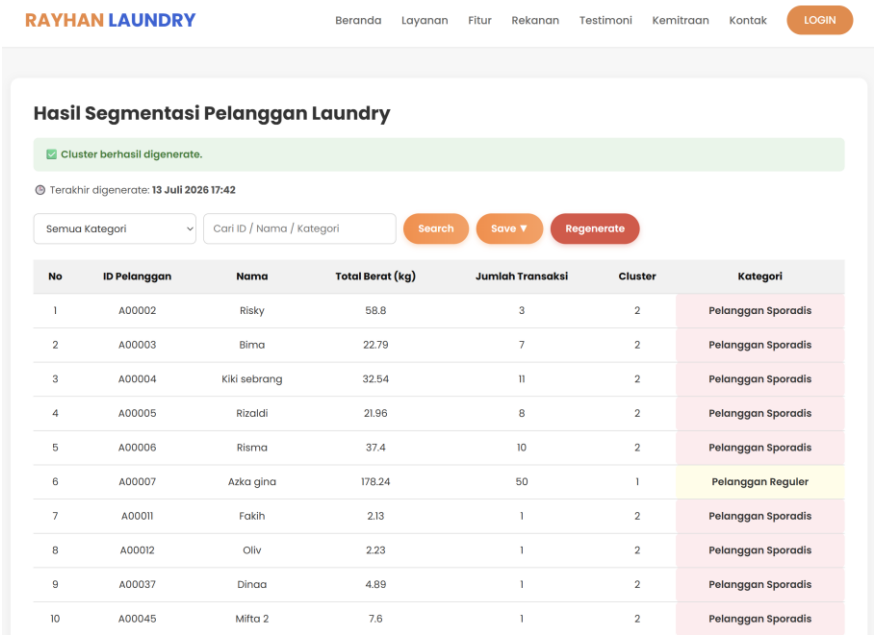


Figure 4 Customer segmentation dashboard in the Rayhan Laundry web application

The dashboard provides search and category-filtering functions to facilitate the examination of specific records and customer segments. Pagination organizes the displayed records into pages of up to 25 entries, while PDF and CSV export functions support the retrieval of segmentation results for reporting and further analysis. A regeneration function is also provided to initiate the clustering workflow through the application.

These functions demonstrate how the analytical results were made accessible through the existing web application. The integration connects the data-processing workflow with an interface through which users can inspect and retrieve the resulting segments. Nevertheless, the presence of these functions does not by itself establish that the system has improved customer retention, revenue, or promotional outcomes. Such effects would require a separate evaluation using operational or business-performance data.

3.5. Functional Validation Using Blackbox Testing

Functional validation of the integrated module was conducted utilizing a black-box testing methodology. This approach evaluates system compliance with specified requirements by comparing actual outputs against expected behaviors, independent of the underlying source code architecture. The test suite encompassed 10 critical scenarios, including cluster generation, data rendering, filtering, search operations (including edge cases like empty/invalid inputs), pagination, export functionalities, and workflow regeneration. The comprehensive results are detailed in Table 2.

Table 2 Blackbox testing results

Test Code	Tested Feature	Test Scenario	Expected Result	Status
BB-01	Generate Cluster	The user selects the Generate Cluster function.	System processes data and displays segmentation results.	Successful
BB-02	Result Display	The user opens the generated results page.	System displays ID, name, weight, frequency, cluster, and category.	Successful
BB-03	Category Filter	The user selects a customer category.	System displays data strictly matching the selected category.	Successful
BB-04	Search	The user enters a supported search keyword.	System displays data matching the query keyword.	Successful
BB-05	Search Input Variation	The user submits an empty or invalid keyword.	System displays all data (empty) or no unrelated data (invalid)	Successful
BB-06	Reset	The user resets the search or filter.	System reverts to the complete, unfiltered segmentation display.	Successful
BB-07	Pagination	The user navigates between result pages.	System displays data for the selected page (max 25 records).	Successful
BB-08	PDF Export	The user exports the segmentation results as a PDF file.	System successfully downloads the report in PDF format.	Successful

BB-09	CSV Export	The user exports the segmentation data as a CSV file.	System successfully downloads the data in CSV format.	Successful
BB-10	Regenerate	The user selects the Regenerate function.	System redirects to the initial Generate Cluster interface.	Successful

All ten test cases yielded successful outcomes, confirming that the implemented features operate in strict accordance with their design specifications. These successful outcomes align with previous studies that advocate for the combined use of Equivalence Partitioning and Boundary Value Analysis to ensure comprehensive functional coverage in information systems [15], [16]. This validates the functional integrity of the system's core data retrieval, navigation, and export mechanisms. However, it must be acknowledged that black-box testing is inherently constrained by the scope of the predefined test cases. While it confirms functional conformity under tested conditions, it does not guarantee exhaustive coverage of all possible edge cases or system configurations, necessitating continuous quality assurance in live environments.

3.6. Usability Evaluation Using the System Usability Scale

Perceived system usability was quantified utilizing the System Usability Scale (SUS), a standardized ten-item instrument designed to evaluate user experience [11]. Following interaction with the segmentation module, 10 respondents completed the SUS questionnaire. The individual and aggregate usability scores are presented in Table 3.

Table 3 System Usability Scale results

Respondent	SUS Score	Usability Category
R1	75.0	Good
R2	100.0	Excellent
R3	77.5	Good
R4	82.5	Excellent
R5	72.5	Good
R6	87.5	Excellent
R7	77.5	Good
R8	90.0	Excellent
R9	72.5	Good
R10	92.5	Excellent
Average:	82.75	Excellent

The module achieved an average SUS score of 82.75, which categorizes it as "Excellent" and significantly surpasses the industry-standard benchmark of 68. This indicates that users found the interface highly intuitive and effective for accessing and interpreting the segmentation data. The dashboard's structured layout and integrated utility functions likely contributed to this positive reception by abstracting the complexity of the underlying clustering algorithms.

Nevertheless, the evaluation has inherent limitations. The SUS score reflects perceived usability rather than objective task efficiency or long-term adoption rates. Furthermore, the sample size of 10 respondents, while sufficient for an initial heuristic evaluation, limits the statistical generalizability of the findings. Future usability studies should incorporate larger, more diverse user cohorts and employ complementary metrics, such as task completion rates, to provide a more holistic assessment of the user experience.

4. CONCLUSIONS

This study successfully developed and implemented a web-based customer segmentation system for Rayhan Laundry utilizing Agglomerative Hierarchical Clustering (AHC). By processing 13,904 historical transaction records, the research aggregated the data into 1,528 distinct customer profiles characterized by two primary behavioral metrics, total laundry weight and transaction frequency. Following feature standardization, the AHC algorithm, configured with Euclidean distance and Ward linkage, partitioned the customers into three distinct clusters. The structural validity of this segmentation was corroborated by a Silhouette Score of 0.753, demonstrating robust cluster separation and cohesion under the applied methodology.

The empirical analysis yielded three actionable customer segments: high-volume (36 customers), regular (209 customers), and sporadic (1,283 customers). This stratification provides a comprehensive behavioral overview of the consumer base, thereby facilitating targeted and differentiated service planning. To operationalize these insights, the segmentation model was seamlessly integrated into a Laravel-based web application. System evaluation confirmed its technical and functional robustness, with all ten black-box test scenarios passing successfully. Furthermore, usability assessments conducted via the System Usability Scale (SUS) resulted in an average score of 82.75, classifying the interface as "Excellent." While these outcomes affirm the system's technical feasibility and high perceived usability, it is important to note that they do not inherently quantify direct improvements in business metrics such as customer retention, revenue generation, or promotional efficacy.

Despite its contributions, this research is subject to certain limitations, including the reliance on only two behavioral variables, the utilization of data from a single enterprise over a specific observation period, the imposition of a fixed cluster count, and a relatively small sample size for the SUS evaluation. To address these constraints and expand upon the current findings, future research should investigate the temporal stability of the segmentation model and conduct comparative analyses with alternative clustering algorithms. Additionally, subsequent studies could enhance the feature space by incorporating variables such as transaction recency, specific service preferences, and customer expenditure. Finally, conducting usability evaluations with larger, more diverse cohorts, alongside longitudinal assessments of actual business performance, will be instrumental in fully establishing the practical and strategic value of the proposed system.

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REFERENCES

[1] A. R. Ramdhanty and Muslim, "The Influence of Service Quality, Customer Trust and Customer Satisfaction on Customer Loyalty for Laundry Services," *Int. J. Econ. Manag. Account.*, vol. 2, no. 1, pp. 31–42, 2024, doi: 10.47353/ijema.v2i1.143.

[2] Y. Syahra, A. Fadlil, and H. Yuliansyah, "Customer Segmentation Using RFM and K-Means Clustering to Support CRM in Retail Industry," *Sink. J. dan Penelit. Tek. Inform.*, vol. 9, no. 3, pp. 1120–1131, 2025, doi: 10.33395/sinkron.v9i3.14907.

[3] O. N. Akande, E. O. Asani, and B. T. Dautare, "Customer Segmentation through RFM Analysis and K-means Clustering : Leveraging Data-Driven Insights for Effective Marketing Strategy," *Ceddi J. Inf. Syst. Technol.*, vol. 3, no. 1, 2024, doi: 10.56134/jst.v3i1.81.

[4] B. I. Nugroho, A. Rafhina, P. S. Ananda, and G. Gunawan, "Customer segmentation in

sales transaction data using k-means clustering algorithm," *J. Intell. Decis. Support Syst.*, vol. 7, no. 2, pp. 130–136, 2024, doi: 10.35335/idss.v7i2.236.

[5] S. Kumar, R. Rani, S. K. Pippal, and R. Agrawal, "Customer segmentation in e-commerce : K-means vs hierarchical clustering," *TELKOMNIKA (Telecommunication Comput. Electron. Control.*, vol. 23, no. 1, pp. 119–128, 2024, doi: 10.12928/telkomnika.v23i1.26384.

[6] I. K. Y. Triantara, M. A. Raharja, and I. B. G. Sarasvananda, "Segmentasi Pelanggan Berbasis RFMT Menggunakan K-Means dan Hierarchical Clustering," *JNATIA (Jurnal Nas. Teknol. Inf. dan Apl.*, vol. 3, no. 4, pp. 917–924, 2025, doi: 10.24843/JNATIA.2025.v03.i04.p22.

[7] A. Afzal *et al.*, "Customer Segmentation Using Hierarchical Clustering," in *2024 IEEE 9th International Conference for Convergence in Technology (I2CT)*, Pune, India: IEEE, 2024, pp. 1–6. doi: 10.1109/I2CT61223.2024.10543349.

[8] G. Ramadhan and Y. Astuti, "Perbandingan Kinerja Algoritma K-means dan Agglomerative Clustering Untuk Segmentasi Penjualan Online Pada Customer Retail," *JPIT (Jurnal Inform. J. Pengemb. IT)*, vol. 9, no. 1, pp. 92–96, 2024, doi: 10.30591/jpit.v9i1.5735.

[9] A. Wasilewski, K. Juszczyszyn, and V. Suryani, "Multi-factor evaluation of clustering methods for e-commerce application," *Egypt. Informatics J.*, vol. 28, p. 100562, 2024, doi: 10.1016/j.eij.2024.100562.

[10] C. P. Ufeli, M. U. Sattar, R. Hasan, and S. Mahmood, "Enhancing Customer Segmentation Through Factor Analysis of Mixed Data (FAMD)-Based Approach Using K-Means and Hierarchical Clustering Algorithms," *Inf.*, vol. 16, no. 6, pp. 1–25, 2025, doi: 10.3390/info16060441.

[11] R. Yani, I. Nazhifah, and M. I. Pradika, "System Usability Scale in Information System Application Development Using Systematic Mapping Study," *IJATIS Indones. J. Appl. Technol. Innov. Sci.*, vol. 2, no. 2, pp. 130–140, 2025, doi: 10.57152/ijatis.v2i2.2275.

[12] A. Jailani and M. A. Yaqin, "Pengujian Aplikasi Sistem Informasi Akademik menggunakan Metode Blackbox dengan Teknik Boundary Value Analysis," *JACIS J. Autom. Comput. Inf. Syst.*, vol. 4, no. 2, pp. 60–66, 2024, doi: 10.47134/jacis.v4i2.78.

[13] M. S. R. Langit, A. Voutama, and A. A. Ridha, "BLACK BOX TESTING PADA WEBSITE SISTEM PERPUSTAKAAN MENGGUNAKAN METODE EQUIVALENCE PARTITIONING DAN ANALISIS BOUNDARY VALUE," *STRING (Satuan Tulisan Ris. dan Inov. Teknol.*, vol. 8, no. 3, pp. 355–364, 2024, doi: 10.30998/string.v8i3.19529.

[14] B. N. Yulisasih, Herman, Sunardi, and H. Yuliansyah, "Evaluation of K-Means Clustering Using Silhouette Score Method on Customer Segmentation," *Ilk. J. Ilm.*, vol. 16, no. 3, pp. 330–342, 2024, doi: 10.33096/ilkom.v16i3.2325.330-342.

[15] M. R. Maulana, E. B. Susanto, and P. A. Christianto, "Pengujian Black Box dengan Teknik Equivalence Partitioning pada Aplikasi Monitoring Pemberian Obat Filariasis Berbasis Android," *KLIK Kaji. Ilm. Inform. dan Komput.*, vol. 4, no. 4, pp. 2179–2187, 2024, doi: 10.30865/klik.v4i4.1603.

[16] F. I. Pratama, E. M. N. Subroto, R. M. Haira, and M. A. Yaqin, "PENGUJIAN BLACK BOX PADA APLIKASI E-COMMERCE OPENCART DENGAN METODE EQUIVALENCE PARTITIONING DAN BOUNDARY VALUE ANALYSIS," *J. Ilm. Inform.*, vol. 8, no. 1, pp. 54–64, 2023, doi: 10.35316/jimi.v8i1.54-64.