Quantifying Digital Transformation Impact on Customer Service Automation in SMEs Using Knowledge Management Approach

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Abstract
Digital transformation (DT) has significantly impacted business operations and customer service, particularly through the rise of automation. This study quantified the influence of DT on customer service automation in small and medium-sized enterprises (SMEs) and predicted open innovation patterns using a hybrid approach. A combination of quantitative and qualitative analysis methods was employed to assess the extent of DT in SMEs and its impact on automating customer service processes. Data were collected from SMEs through surveys and interviews, using convenience sampling to gather insights on their adoption of digital technologies and automation levels. The study found that effective knowledge management practices are crucial for SMEs to successfully implement these technologies, enabling them to acquire, store, transfer, and utilize knowledge generated from customer interactions. Additionally, a predictive model was developed to identify open innovation patterns, combining machine learning algorithms with expert knowledge. The hybrid approach leveraged the power of automated data analysis alongside professional domain expertise. The utilization of a Morphological-Linear Neural Network (MLNN) in conjunction with a Logistic Regression model demonstrated effectiveness in addressing complex pattern recognition and prediction tasks. The analysis, conducted using SPSS software, revealed that SMEs could enhance customer satisfaction by aligning their DT strategies with customer-centric approaches. The findings offer valuable insights for SMEs, guiding their DT strategies to drive more effective and efficient customer service operations.

Keywords: Digital Transformation, Customer Service Automation, Predicting Open Innovation, Hybrid Approach, Small and Medium-sized Enterprises (SMEs), and Convenience Sampling Method.

1. INTRODUCTION

For small and medium-sized enterprises (SMEs), effective knowledge management is a cornerstone of sustainable growth and competitiveness. SMEs, often characterized by resource constraints and dynamic environments, must leverage their knowledge assets to remain agile, innovative, and customer-centric [1-2]. Knowledge management in SMEs involves systematically capturing, organizing, storing, retrieving, and disseminating information and expertise within the organization. In today's fast-paced business landscape, digital transformation (DT) has emerged as a pivotal driver of success, especially for SMEs [3-4]. The impact of DT on customer service and the ability to predict open innovation patterns are particularly significant in this context. This study comprehensively explores the profound influence of DT on customer service automation within SMEs [5-6]. The complex interaction between technological advancements and customer service practices necessitates a nuanced understanding, prompting the adoption of a hybrid approach that integrates various methodologies for a holistic assessment [7-8]. Open innovation, facilitated by digital ecosystems, has become essential for SMEs seeking collaborative solutions and external partnerships. This research integrates predictive modeling techniques to forecast how SMEs are likely to engage in open innovation practices [9-10]. By leveraging data-driven methodologies and incorporating qualitative insights, the study aims to provide actionable guidance for SMEs navigating the complex landscape of DT and open innovation [11-12].

As SMEs increasingly integrate digital technologies into their operations, understanding the impact of these changes on customer service becomes imperative. This includes evaluating how automation, driven by DT initiatives, influences service delivery, responsiveness, and overall customer satisfaction [13]. The hybrid approach adopted in this study encompasses both quantitative metrics and qualitative insights, ensuring a comprehensive evaluation that captures the multifaceted nature of DT in SMEs. As businesses strive to streamline operations, enhance customer experiences, and reduce costs, the automation of customer service has emerged as a game-changer. This transformation enables SMEs to manage routine tasks efficiently, ensuring seamless and personalized interactions with customers [14]. However, the successful implementation of customer service automation is heavily dependent on effective knowledge management practices, which allow SMEs to harness the wealth of knowledge generated through customer interactions. Additionally, open innovation practices are gaining prominence as SMEs recognize the value of collaborating with external partners, including other businesses, research institutions, and customers. Understanding how high customer satisfaction ratings influence brand perception and consumer behavior is critical in this context [15].The objective of this study is to quantify the effect of DT on customer service automation and predict open innovation patterns in SMEs using a hybrid approach. The remaining sections are arranged as follows: The literature review was described in Section 2, the study problem identification and motivation were described in Section 3, the proposed technique was described in Section 4, the results were discussed in Section 5, and the paper's conclusion was described in Section 6.

2. LITERATURE SURVEY

The literature survey concentrates on assessing the impact of Digital Transformation (DT) on customer service automation and predicting open innovation patterns in SMEs. This exploration evaluates the influence of DT on automated customer service and forecasts innovative patterns within the context of SMEs. Srisathan et al [16] elucidated the implementation of open innovation processes by SMEs, emphasizing two critical aspects: open innovation implementation and ambidextrous innovation practices. The study highlights the necessity for SMEs to adopt open innovation strategies for sustained growth and provides strategic insights based on empirical findings. Skare et al. [17] offered key perspectives on the implications of DT for European SMEs, contributing significantly to understanding how DT influences SMEs' business models, managerial practices, competitiveness, and overall business activities. This research underscores the transformative potential of DT in reshaping the operational landscape of SMEs. Martínez-Peláez et al. [18] examined how SME owners or senior managers can initiate sustainable DT projects, identifying essential organizational capabilities required for successful transformation. This study delineates the initial steps that SME leaders can take to foster effective DT implementation. Putri et al. [19] explored the impact of DT on SME revitalization during the COVID-19 pandemic by surveying 278 SME respondents in Bukittinggi. The findings revealed a significantly positive effect of DT on SME revitalization, emphasizing the critical role of digital transformation in SME recovery during challenging periods. The study also recommends enhancing digital education to support this transformation. Kumar et al. [20] stressed the importance of SMEs exploring and identifying enablers to enhance their DT processes. Their research utilized F-ISM and MICMAC analysis to reveal four pathways for SMEs to become digitally resilient in the current dynamic environment. These pathways provide practical guidance for SMEs aiming to strengthen their digital capabilities. Wu et al. [21] conducted multiple case studies involving interviews and archival data from four manufacturing firms with open innovation enabled by digital capabilities. Their research contributes two key insights to the existing literature: it elucidates the internal mechanisms through which digital capabilities drive open innovation from a resource integration perspective and provides a theoretical reference for digital transformation and open innovation practices in manufacturing enterprises. Songkajorn et al. [22] investigated the role of organizational strategic intuition (OSI) and its relationship with knowledge-based dynamic capabilities (KBDCs), DT, and high-performance organizations. The empirical findings expand the understanding of strategic intuition and its influence on organizational performance within the context of DT. Valdez-Juárez et al. [23] analyzed the effects of business strategy (financial and market) and innovation management on the economic indicators and performance of SMEs in Sonora, Mexico. The results indicated that business strategy, whether financial or market-focused, does not significantly impact innovation management or the economic performance of SMEs in this region. Caparida et al. [24] assessed customer satisfaction levels regarding online shopping. The study revealed high satisfaction among respondents, particularly concerning convenience, product delivery, and quality, all of which significantly contribute to overall customer satisfaction in the online shopping context. Sudirjo et al. [25] evaluated the level of customer care provided through e-banking platforms, employing questionnaires, interviews, and observations to gather data. The analysis presents an intriguing picture of e-banking usage, showing balanced gender distribution among respondents, with men constituting 40% and women 60% of the total sample. Evaluated the level of customer care offered online so that users can keep using the e-banking system as they see fit. To gather data for the e-banking system study, involved parties' questionnaire responses, interviews, and observations are used [26-31]. The data analysis shows quite an interesting picture regarding the use of e-banking by respondents in this study. In terms of gender distribution, it appears that there is no significant dominance between men and women, with men (40%) and women (60%) of the total respondents.

3. RESEARCH PROBLEM DEFINITION AND MOTIVATION

DT and Open Innovation Strategies in SMEs can revolutionize their approach to KM. It empowers SMEs to become more innovative, customer-centric, and adaptable in a rapidly changing business environment. To expand the commitment of these methodologies, SMEs have to foster an extensive computerized change guide, encourage a culture of open development, and put resources into the right computerized instruments and innovations. Information is an imperative resource for associations, particularly in the present Business 4.0 setting. Information the executives (KM), which concerns the exercises of information securing and abuse, are moderately very much applied in enormous associations. Nonetheless, SMEs are confronting assorted hindrances. Customary KM techniques for the most part give a structure that isn't versatile to the SME setting because SMEs present specificities that recognize them from enormous associations. Regardless of possibly enormous advantages, little and medium-sized undertakings (SMEs) slack in the advanced change. Arising advancements, however various as they seem to be, offer a scope of uses for them to further develop execution and defeat the size-related restrictions they face in carrying on with work. Nonetheless, SMEs should be more ready, and the stakes are high.

The SME computerized hole has expanded disparities among individuals, places and firms, and there are worries that the advantages of the advanced change could gather early adopters, further widening these imbalances. Many SMEs struggle to keep up with the rapidly evolving digital landscape. They may lack the technology infrastructure and expertise needed to automate customer services, which can result in suboptimal customer experiences. SMEs may find it challenging to tap into external knowledge sources and innovation networks. They often operate in isolation, missing out on opportunities for collaboration and access to external expertise. The lack of seamless integration can hinder efficiency and data flow within the organization. Open innovation can enable SMEs to access new sources of ideas, technologies, skills, and markets, and to overcome their resource constraints and competitive disadvantages. This exploration study investigates the piece of computerized change and open development in further developing administration proficiency in SMEs.

4. PROPOSED RESEARCH METHODOLOGY

SMEs often face challenges in efficiently capturing, organizing, and leveraging their internal knowledge resources. This leads to inefficiencies, missed opportunities, and the risk of losing valuable institutional knowledge. SMEs that effectively manage their knowledge resources achievementas a modestbenefit by making informed decisions, fostering innovation, and responding to customer needs more efficiently. The problem at hand revolves around enhancing knowledge management, facilitating DT for customer service automation, staying updated with open innovation trends in knowledge sharing, and achieving seamless integration. SMEs often face challenges related to knowledge silos, manual customer service processes, limited knowledge sharing, and fragmented systems and processes.

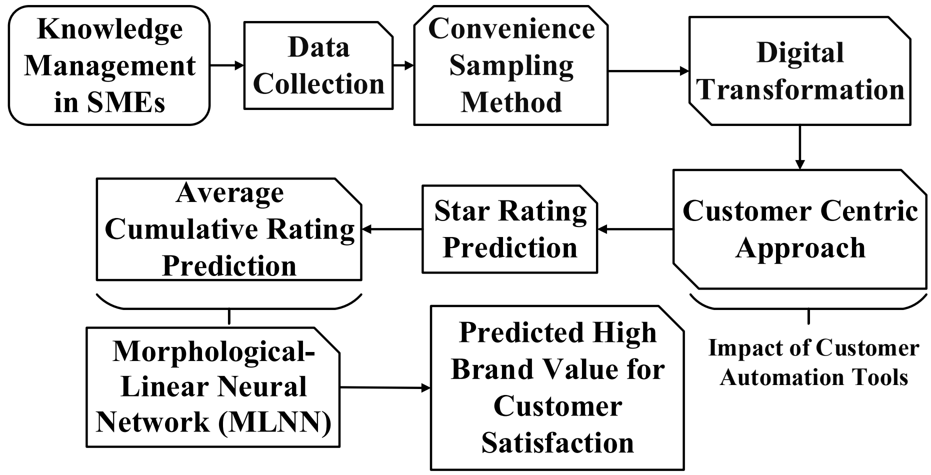

Figure 1: Block Diagram of the Proposed Work

Figure 1 shows the block diagram of the proposed work. The data was collected from the various purchasing websites for online clothing. The convenience sampling method is used for the collection of data. However, to successfully implement these technologies, SMEs need to adopt effective knowledge management practices that can enable them to acquire, store, transfer, and exploit the knowledge generated from their interactions with customers driven by a customer-centric approach. Data will be obtained from a trial of SMEs through surveys and interviews to gather information on their adoption of digital technologies and the level of automation in their customer service processes. The utilization of Morphological-Linear Neural Network (MLNN) in conjunction with a Logistic Regression model for addressing complex pattern recognition and prediction tasks. This study predicts the high ratings of brands for the base of customer satisfaction. The highest brand is predicted for this study on the base of customer satisfaction.

4.1 Data Collection

Online clothing was used to collect data from customers of online modest fashion on Instagram. Instagram was selected for the study among the other social media platforms because it is believed that Instagram offers a fertile environment for the fashion industry owing to its dependence on visual content and images. Additionally, it was stated by Barnhart that Instagram has the highest engagement rates among social media platforms. The examples were chosen utilizing the convenience sampling method. Accommodation inspecting is utilized because of its usability and is more straightforward for specialists to acquire information disregarding a few perspectives, like the utilization of randomized testing. The focus of the study was on primary data. The questionnaire was administered to experts in various agencies related to the SME industry. The responses were collected using a 7-point Likert scale, which is the most reliable of the Likert scales as it captures the best sentiment of the respondent.

Attributes of the Study

The development of online fabric shopping has radically expanded due to its helpful elements and efficient. In prior times, it was not well known to purchase all garments from web-based promoting, however assuming that the quick development of advanced advertising is arising and acquiring consideration by everybody. At present situation barely anybody goes to nearby stores to buy articles of clothing. It has become a pattern now to pick computerized showcasing for shopping it has different elements to serve you best. Internet clothing stores are normal these days, everybody knows that shopping online is very simple and efficient.

Table 1: Criteria for Evaluating Digital Transformation Impact and Customer Satisfaction in SMEs

Variables	Criteria	Explanation
Knowledge Management (KM)	**C1:** Sense-making, Decision Making & Innovation	The designers' conceptual frameworks they employed to make sense of their fashion behaviour.
	C2: Agency and shipment	An individual or organization whose occupation is to manage plans and records for sending products starting with one spot and then onto the next.
	C3: Information Management	It gives data expected for vital preparation and everyday tasks.
Customer Service Automation (CSA)	**C1:**Improve efficiency	The right computerization apparatus assists organizations with offering fast and important reactions to inquiries through different channels with fewer blunders and slip-ups.
	C2: Cost-effective	Traditional support demands more human involvement, training, cost, and time.
Digital Transformation Initiatives (DTI)	**C1:**Pre-planning	Time is it suitable to commit to arranging a long-term project that will affect the association.
	C3: Business visioning	Business visioning portrays a course of looking at the ongoing circumstancesand recognizing the difficulties you want to survive.
User Satisfaction (US)	**C1:**Meeting Customer	The base, necessity that is asked of you to support the market is the capacity to live up to the assumptions of a client.
	C2: Surpassing Customer	A well-disposed client care that gives off-the-cuff arrangements, trailed by standard criticism meetings could put you at this level.
Customer Experiences (CE)	**C1:** Direct customer experience	This incorporates the buying lifecycle, the experience of utilizing the item or administration, and any collaboration they have with the group
	C2: Indirect customer experience	It alludes to the uninvolved experiences with your organization. This can be the advertising endeavours and outside promotion or resistance, like audits, verbal correspondence, and outer media inclusion.
Collaboration and Communication (CC)	**C1:** Team Collaboration	Each person knows what their role on the team involves and how it impacts other team members.
	C2: Network Collaboration	The network members collaborate virtually without necessarily knowing each other personally. Members may post links to websites they find helpful using a social bookmarking tool.

Employees' Comfort Level (ECL)	**C1:** Employee Satisfaction and Work Environment	The level of comfort and satisfaction experienced by employees within their work environment. Higher ECL indicates that employees feel valued, supported, and motivated, leading to increased productivity and job satisfaction.
	C2: Comfort Level	The level of comfort experienced by employees within the work environment, temperature control, noise levels, and overall satisfaction with their workspace.
Knowledge Sharing (KS)	**C1:** Information Dissemination	The exchange and dissemination of information, ideas, and expertise among individuals or groups within an organization.
	C2: Collaboration	Higher levels of knowledge sharing indicate a culture of collaboration, transparency, and continuous learning within the organization and organizational performance.
Change Fatigue (CF)	**C1:** Adaptation	CF reflects the capacity of individuals or organizations to adapt to changes effectively while maintaining productivity and well-being.
	C2: Resilience	Understanding CF is essential for assessing the impact of organizational changes and implementing strategies to mitigate fatigue and support resilience.
Job Security (JS)	**C1:** Stability	Job Security (JS) measures the perceived stability and continuity of employment within an organization. It encompasses factors such as the likelihood of layoffs, contract renewals, and organizational stability.
	C2: Continuity	Higher Job Security scores indicate greater confidence among employees in the longevity of their positions, leading to reduced stress and increased commitment to the organization.

Table 1 shows the variables outlined encompass different aspects crucial for assessing the effectiveness and impact of various initiatives within the fashion industry, ranging from knowledge management to customer service automation, DT, user satisfaction, customer experiences, and collaboration and communication. Each criterion provides specific criteria and explanations to evaluate different facets of these initiatives, such as sense-making in knowledge management, efficiency and cost-effectiveness in customer service automation, and direct versus indirect customer experiences. By considering these variables comprehensively, stakeholders can gain insights into the effectiveness of their strategies and identify areas for improvement to enhance overall performance and customer satisfaction in the fashion industry.

Hypothesis of the Study

H1: There is a significant positive relationship between the implementation of DT initiatives and the efficiency of customer service in SMEs.

H2: There is a significant positive relationship between knowledge sharing among employees and the success of DT initiatives in SMEs.

H3: The use of customer service automation tools contributes to a significant reduction in operational costs related to customer service in SMEs.

H4: Familiarity with customer service automation tools positively affects employees' comfort levels in SMEs.

H5: There is a significant association between DT initiatives and employees' resistance to change (change fatigue) in SMEs.

H6: User-friendly interfaces significantly affect the success of DT initiatives in SMEs, enhancing user satisfaction and job security.

H7: Facilitating collaboration and communication through automation tools significantly affects the success of DT initiatives in SMEs.

This hypothesis posits that knowledge management practices play a pivotal role in the success of DT initiatives within SMEs, particularly in the context of customer service automation. It suggests that the comprehensive implementation of these knowledge management practices can lead to improved outcomes in terms of automation effectiveness, operational efficiency, and customer satisfaction. Researchers can use this hypothesis as a foundation for empirical investigations into the relationship between knowledge management practices and the outcomes of DT efforts in SMEs.

4.1.1Convenience Sampling Method

Convenience sampling is a non-probability sampling method widely employed in research for its practicality and efficiency. In this approach, participants are chosen based on their easy convenience and handiness to the investigator, fairly than through a random selection process. This way is frequently utilized when time, resources, or constraints make it challenging to implement more complex sampling techniques. Researchers employing this method typically select contributorsgrounded to proximity, convenience, or affiliation, making it a pragmatic choice for studies with practical constraints or when a quick and accessible sample is essential. A convenience sampling method was employed for sample selection, utilizing a semi-structured questionnaire survey with the support of a company. Convenience sampling involves selecting participants based on their easy availability and contiguity to the researcher. In this circumstance, the researchers chose respondents who were readily available and accessible, likely due to their affiliation with various professional associations of businesses in SMEs. This sampling method is practical and efficient, especially when the researchers aim to gather data from a specific population within the SME sector. The study collaboratively worked with a company to facilitate the survey process. This collaboration could involve logistical support, access to potential participants, or other resources that the company could provide. By targeting professional associations within the SME domain, the study aims to capture insights from a diverse range of professionals who are likely to have valuable perspectives on the subject under investigation. This approach not only simplifies the sampling process but also leverages existing networks and associations to enhance the relevance and representativeness of the gathered data.

4.2 Digital Transformation

DT for SMEs is the automation of customer services, which can streamline and simplify routine tasks, improve customer experience, and reduce costs. Automation of customer services is becoming essential in delivering seamless and personalized experiences. It is determined by a customer-centric approach are actively exploring avenues to automate everyday operational processes, intending to elevate their customer interactions to a higher level. However, to successfully implement these technologies, SMEs need to adopt effective knowledge management practices that can enable them to acquire, store, transfer, and exploit the knowledge generated from their interactions with customers. The method utilized the learning in a descriptive analysis from a qualitative perspective. The study defines qualitative research as an approach to learning about and making sense of the different weights that various people and groups place on job insecurity, lack of familiarity, and change fatigue with various knowledge management practices.

4.2.1 Customer-Centric Approach

SMEs are increasingly embracing a customer-centric methodof digital alteration as they seek to enhance operational efficiency and customer interactions. The leveraging digital technologies, SMEs can automate routine tasks, allowing for streamlined processes and resource optimization. This customer-centric DT involves the integration of digital tools and platforms that prioritize the needs and preferences of customers, ultimately leading to improved service delivery. As SMEs direct the difficulties ofthe modern business landscape, adopting a customer-centric approach becomes instrumental in staying competitive and responsive to evolving market demands. In this transformative journey, knowledge management plays a pivotal role for SMEs. It enables them to effectively acquire, store, transfer, and exploit the knowledge generated from their interactions with customers. This knowledge encompasses insights into customer behaviours, preferences, and feedback, providing SMEs with valuable information to tailor their products or services. By effectively managing and leveraging this knowledge, SMEs can not only enhance their customer-centric initiatives but also build a foundation for up-to-datechoicecreation along with sustainable growth. In essence, the combination of a customer-centric DT strategy and robust knowledge management empowers SMEs to thrive in a dynamic business environment.

4.3 Star Rating Prediction

Consumers considering purchasing clothing items from Avant-Garde Apparel, Vogue Venture, Ethereal Ensembles, Chic Creations, or Rare Raiment can greatly benefit from online evaluations. Similar to reviews on platforms like TripAdvisor, these evaluations typically consist of text feedback posted under each clothing item or brand, accompanied by star ratings ranging from 1 to 5. These ratings serve as a quick indicator of customer satisfaction, helping shoppers make informed decisions about their purchases. Rating prediction (RP) techniques can be applied to forecast the star ratings associated with each clothing item or brand, providing valuable insights for both consumers and brand managers. By analyzing sentiment and star ratings, businesses can enhance the effectiveness of their recommendation systems and improve overall customer satisfaction.

4.3.1 Average Cumulative Rating Prediction

Examining the relationship between freedom of destination, satisfaction, and choice loyalty will help the study evaluate a model, and the satisfaction of user preference by analysing the cumulative rating prediction model. The calculated sentiment score and star ratings are combined to predict the best destination for the user. Average cumulative prediction helps to find the personalized search results from the value. The obtained sentiment score S_1 is 4.0 and the star rating S_2 value will be 3. Thus the cumulative average S_1 and S_2 variable S are defined as follows.

$$Average\ Cumulative\ Rating = \frac{Sentiment\ Score + Star\ Rating}{2} \tag{1}$$

$$S = \frac{S_1 + S_2}{2} \tag{2}$$

$$S = \frac{4.0 + 3}{2} = \frac{7}{2} = 3.5 \tag{3}$$

Simply stated, the sentiment score and star rating's mean is the cumulative mean of an element in a variable. The value of 3.5 will be the average of both ratings. Further, a method is also tested which makes use of these SO scores for each review along with tokens and their SO values as independent variables for ML models built using training data are then used to classify reviews in the test set. MLNN is used for this building of the ML model as it is among the most effective algorithms in polarity classification tasks across studies. It uses the overall SO score of each review calculated as well using the mean of SO scores across all selected words used in that review based on their sentiment scores calculated in the selected sentiment lexicon. The reviews are counted once the lexicons are built using exercise data, and these marks are then used as extra inputs together with review unigrams for training MLNN for classification.

Morphological-Linear Neural Network (MLNN)

The model combines two different kinds of neural layer types: a hidden layer finished up of MNs and classical perceptron neurons generated by the output layer. The model can distinguish between various patterns by using hyperplanes and hyperboles on the components of MNs and perceptron, respectively. Stochastic gradient descent (SGD) was used to train this hybrid model in its entirety. Finally, using this hybrid design, compare multilayer perceptrons and DMNs. With the following equation, the network model may be defined:

$$Y(x)=\rho\left(\sum_{i=1}^{k} w_i f_i(x)+b\right) \tag{4}$$

Where, ρ is the sigmoid function for two classes, and a Softmax function for the case of N classes. i Denotes the MNs in the middle layer; the following $f_i(x)$ are MNs, as specified by Equations 4 and 5. Another aspect of the architecture that stands out is the fact that it just has one intermediate layer, and the MNs, which is sufficient to classify a wide range of datasets. Figure 2 depicts the network's architecture. The squares in this diagram represent the MNs that Equations 4 and 5 define.

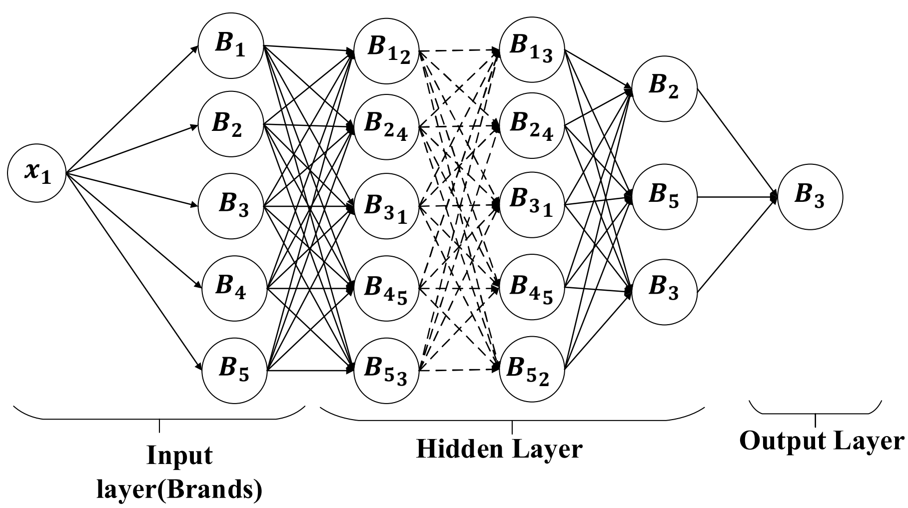

Figure 2: Morphological Linear Neural Network Architecture

Figure 2 illustrates the Morphological Linear Neural Network Architecture, which comprises an input layer with five units representing brands: B1-Avant-Garde Apparel, B2-Vogue Venture, B3-Ethereal Ensembles, B4-Chic Creations, or B5-Rare Raiment. The hidden layer consists of one layer with two units, employing the hyperbolic tangent activation function. Finally, the output layer is dedicated to B3-Ethereal Ensembles.

Morphological neurons are employed in the classification layer, where one necessity exists for each class to be classified. This occurs because each MN's weight encloses a class's patterns, necessitating a similar amount of MNs at the output layer for all classes T .

$$f(x)=W_N^T\rho\left(W_{N-1}^T\rho\right)\left(\cdots W_1^T\rho\left(W_0^T\right)\right) \tag{5}$$

The function composition which is the outcome of stacking layers of perceptron-type neurons is represented by equation 7. Where X denotes the input vector, W_N indicates the synaptic weights matrix of the layer's perceptron-type neurons, and ρ specifies the activation function in this case. The following describes the t -th MN.

$$y_t(x)=h_t(f(x)) \tag{6}$$

A Softmax-type layer, the final component of this architecture, supplies the PD for each training class. These are the equations for this model:

$$O=\rho_0(y(x)) \tag{7}$$

Equation (6) represents the network output whereas Equation (7) represents the Softmax activation function. As a result, ratings accurately categorized the sentiment type based on the travel destination. To achieve the final emotion score, integrate these models' predictions using a multilayer network. Using perceptron neurons determines which evaluation of all the data received the highest score.

5. EXPERIMENTATION AND RESULT DISCUSSION

The effectiveness of informationadministration practices in SMEs in terms of knowledge acquisition, storage, and utilization. The study utilized statistical tests within SPSS to establish the statistical significance of findings, ensuring robust and reliable outcomes. Depending on the research design, the study applies statistical tests to examine relationships, differences, or associations in the data using t-tests, chi-squared tests, and correlation analyses. Further, measures the extent to which open innovation collaborations contribute to SMEs' innovative capabilities. Customer-centric insights gain insights into customer preferences and behaviours through DT data. Accordingly, identify key factors influencing customer service automation in DT.

5.1 Reliability Statistics

Reliability statistics were employed in the study on Customer Service Automation and Predicting Open Innovation Patterns in SMEs to assess the consistency and stability of the measurement instruments used. The reliability analysis included various aspects of the research, such as customer service automation and open innovation patterns, aiming to confirm that the collected data and instruments provided dependable and consistent results. This rigorous approach enhances the credibility and robustness of the study's findings, allowing for more reliable insights into the effectiveness of customer service automation and the factors influencing open innovation practices within SMEs. The reliability statistics contribute to the overall methodological strength of the research, providing a solid foundation for drawing meaningful conclusions and implications for both academia and industry practitioners.

Table 2: Analysis of Reliability Test Results for 11-Item Questionnaire

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.883	.701	11

Table 2 presents the results of the reliability test analysis for the given data set indicating a Cronbach's Alpha of 0.883 and a Cronbach's Alpha based on standardized items of 0.701, with a total of 11 items. Cronbach's Alpha is a quantity of internal consistency or reliability in established items in a questionnaire or survey. In this context, a Cronbach's Alpha of 0.883 suggests a great phase of consistency among the items, indicating that they are measuring the same underlying construct reliably.

Table 3: ANOVA with Friedman's Chi-Square Test Results for Between-People and Between-Item

<table>
<tr><th colspan="2"></th><th>Sum of Squares</th><th>df</th><th>Mean Square</th><th>Friedman's Chi-Square</th><th>Sig</th></tr>
<tr><td colspan="2">Between People</td><td>45189.032</td><td>944</td><td>47.870</td><td></td><td></td></tr>
<tr><td rowspan="3">Within People</td><td>Between Items</td><td>482.087[a]</td><td>10</td><td>48.209</td><td>10.986</td><td>.359</td></tr>
<tr><td>Residual</td><td>414194.822</td><td>9440</td><td>43.877</td><td></td><td></td></tr>
<tr><td>Total</td><td>414676.909</td><td>9450</td><td>43.881</td><td></td><td></td></tr>
<tr><td colspan="2">Total</td><td>459865.941</td><td>10394</td><td>44.243</td><td></td><td></td></tr>
<tr><td colspan="7">Grand Mean = 19.09</td></tr>
<tr><td colspan="7">a. Kendall's coefficient of concordance W = .001.</td></tr>
</table>

Table 3 presents ANOVA with Friedman’s Test the results of a Friedman's Chi-Square test, which is a non-parametric statistical test used to detect differences in treatments across multiple related groups. The framework of this analysis involves both between-people and between-item comparisons. The sum of squares between people is 45189.032, with 944 degrees of freedom, resulting in a mean square of 47.870. The Friedman's Chi-Square value for between items is 10.986, with a significance level (Sig) of 0.359, indicating no case of statistically significant difference between the items.

Table 4: Single and Average Measures for Intraclass Correlation Coefficient

	Intraclass Correlation	95% Confidence Interval		F Test with True Value 0			
		Lower Bound	Upper Bound	Value	df1	df2	Sig
Single Measures	.008[a]	-.001	.018	1.091	944	9440	.033
Average Measures	.083[c]	-.006	.168	1.091	944	9440	.033
Two-way mixed effects model where people effects are random and measures effects are fixed.							
a. The estimator is the same, whether the interaction effect is present or not.							
b. Type C intraclass correlation coefficients using a consistency definition. The between-measure variance is excluded from the denominator variance.							
c. This estimate is computed assuming the interaction effect is absent because it is not estimable otherwise.							

Table 4 shows intraclass correlation coefficients (ICC) presented here providing insights into the reliability of the measurements in the dataset. For single measures, the ICC is 0.008 with a 95% confidence interval between -0.001 and 0.018. This suggests a low level of agreement among the single measures. The F test with a true value of 0 yields a statistically significant result ($p = 0.033$), indicating that there is a significant difference from zero. For average measures, the ICC is 0.083 with a 95% confidence interval between -0.006 and 0.168. This indicates a slightly higher level of agreement when considering average measures. The F test with a true value of 0 is also statistically significant ($p = 0.033$). The two-way mixed effects model, where people's effects are random and measures effects are fixed, is utilized for these calculations.

5.2 Descriptive Statistics

Descriptive statistics were applied to key variables, including Knowledge Management (KM), Customer Satisfaction (CS), Customer Engagement (CE), Employee Commitment to Learning (ECL), Knowledge Sharing (KS), Customer Service Automation (CSA), Decision Trees (DT), User Satisfaction (US), Continuous Feedback (CF), Job Satisfaction (JS), and Communication Culture (CC). The analysis provided summary measures, such as means, standard deviations, and valid case counts, for each variable. This comprehensive approach to descriptive statistics aids in understanding the central tendencies, variabilities, and distributional characteristics of the studied constructs, offering valuable insights into the diminuendos of knowledge supervision, customer service, and employee engagement within the organizational context. The valid case count reflects the number of complete cases considered in the analysis, ensuring the reliability and representativeness of the descriptive statistics for the specified variables.

Table 5: Descriptive Statistics for Specified Variables

	N	Minimum	Maximum	Mean		Std. Deviation	Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic	Std. Error
KM	945	9	31	19.17	.186	5.731	-1.183	.159
CS	945	8	30	19.10	.190	5.846	-1.277	.159
CE	945	7	234	19.14	.296	9.099	328.808	.159
ECL	945	5	129	19.03	.225	6.914	66.271	.159
KS	945	8	36	19.04	.196	6.032	-1.071	.159
CSA	945	7	234	19.67	.298	9.171	315.338	.159

DT	945	4	36	19.01	.188	5.787	-1.113	.159
US	945	5	32	18.96	.192	5.910	-1.175	.159
CF	945	7	36	19.15	.188	5.771	-1.115	.159
JS	945	8	36	18.85	.187	5.739	-1.118	.159
CC	945	5	36	18.83	.189	5.820	-1.072	.159
Valid N (listwise)	945							

Table 5 shows descriptive statistics for various variables in the dataset providing a snapshot of the central tendency and variability of each measure. For the KM variable, the mean is 19.17 with a minimum of 9 and a maximum of 31, indicating a moderate spread around the average value. The CS variable exhibits a similar pattern with a mean of 19.10 and a range between 8 and 30. The CE variable, representing another measure, shows a higher mean of 19.14 with a wider range from 7 to 234. The ECL variable has a mean of 19.03, ranging from 5 to 129. The remaining variables, such as KS, CSA, DT, US, CF, JS, and CC, also display varying means and ranges. The standard deviations provide insights into the dispersion of values around the means for each variable. Additionally, the kurtosis values indicate the shape of the distribution, with negative values suggesting a relatively flatter distribution. These descriptive statistics collectively offer a wide-rangingsynopsis of the distributional characteristics of each variable, facilitating aninitialconsideration of the dataset's features.

5.3 Regression Test Analysis

Regression analysis is a statistical technique used to examine the relationship between one or more independent variables (also known as predictors or features) and a dependent variable (also known as the outcome or response). The goal of the regression analysis is to understand how changes in the independent variables are associated with changes in the dependent variable.

Table 6: Regression Model Summary for Predicting KM

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.199[a]	.040	.029	5.647	2.002
a. Predictors: (Constant), CC, CSA, CF, CE, US, ECL, CS, KS, DT, JS					
b. Dependent Variable: KM					

Table 6shows the model summary provides an overview of the regression model's performance in predicting the dependent variable KM based on the specified predictors. The R square value, representing the percentage of variance in the reliant on variable explained by the predictors, is 0.040, indicating a limited ability of the model to account for the variability in KM. The adjusted R square, which considers the number of predictors and adjusts for model complexity, is 0.029. The standard error of the estimate, measuring the variability of actual values around the predicted values, is 5.647. The Durbin-Watson statistic, assessing the presence of autocorrelation in the residuals, is 2.002, suggesting that there is no significant autocorrelation. The predictors included in the model are CC, CSA, CF, CE, US, ECL, CS, KS, DT, and JS, with a constant term. While the model provides some insight into the relationship between predictors and the dependent variable KM, the relatively low R square indicates that other factors may contribute to the variability in KM not captured by the included predictors. Interpretation and further analysis should consider the limitations and explore potential enhancements to the model.

Table 7: ANOVA[a] Results for Regression Model Predicting KM

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1227.608	10	122.761	3.850	.000[b]
	Residual	29779.975	934	31.884		
	Total	31007.583	944			
a. Dependent Variable: KM						

b. Predictors: (Constant), CC, CSA, CF, CE, US, ECL, CS, KS, DT, JS

Table 7 shows the analysis of variance (ANOVA) results for the regression model predicting the dependent variable KM indicating a statistically significant overall model fit. The sum of squares for the regression is 1227.608, with 10 degrees of freedom, resulting in a mean square of 122.761. The F-statistic is 3.850, and the associated p-value is 0.000, denoted as .000b. This small p-value suggests that one of the predictors in the model is contributing significantly to the prediction of KM. The quantity of squares for the residual, representing unexplained variability, is 29779.975, with 934 degrees of freedom and a mean square of 31.884. Which accounts for the total variability in the reliant-on variable, is 31007.583. These ANOVA results support the conclusion that the regression model, including predictors (Constant), CC, CSA, CF, CE, US, ECL, CS, KS, DT, and JS, provides a statistically significant improvement in explaining the modification in the needy variable KM compared to a model with no predictors. Researchers should further explore the specific contributions of each predictor to the model and assess the sturdiness of the findings.

Table 8: Coefficients Table for Regression Analysis Predicting Variables

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	18.874	1.674		11.275	.000
	CS	.144	.032	.147	4.525	.000
	CE	-.049	.020	-.077	-2.388	.017
	ECL	.047	.027	.057	1.739	.082
	KS	-.013	.031	-.014	-.415	.678
	CSA	-.014	.020	-.022	-.666	.505
	DT	-.037	.032	-.038	-1.152	.249
	US	-.082	.032	-.085	-2.606	.009
	CF	.032	.032	.032	.996	.319
	JS	-.030	.033	-.030	-.921	.357
	CC	.017	.032	.017	.532	.595
a. Dependent Variable: KM						

Table 8 shows the coefficients table for the regression ideal predicting the dependent variable KM reveals valuable insights into the impact of each predictor. The constant term, representing the estimated value of KM when all predictors are zero, is 18.874. Among the predictors, CS positively influences KM, with a coefficient of 0.144 and a significant p-value of 0.000. Conversely, CE shows a negative impact on KM, as reflected by its coefficient of -0.049 and a statistically significant p-value of 0.017. ECL exhibits anoptimisticeffect on KM, with a coefficient of 0.047, although the p-value is 0.082, indicating a marginal level of significance. By the way, KS, CSA, DT, CF, JS, and CC do not suggestivelypay to the prediction of KM, as their associated p-values are greater than the conventional threshold of 0.05. Notably, the US harms KM, with a coefficient of -0.082 and a significant p-value of 0.009. These findings offer a nuanced understanding of the relationships between predictors and KM, guiding further investigation into the underlying dynamics of the studied phenomena.

Table 9: Residual Statistics for Regression Model Predicting

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	10.48	24.34	19.17	1.140	945
Residual	-11.545	12.711	.000	5.617	945
Std. Predicted Value	-7.619	4.538	.000	1.000	945

Std. Residual	-2.045	2.251	.000	.995	945
a. Dependent Variable: KM					

Table 9 displays the residual statistics and provides crucial insights intothe presentation of the regression ideal predicting the dependent variable KM. The predicted values for KM range from 10.48 to 24.34, with a mean of 19.17 and a standard deviation of 1.140. The residuals, representing the differences between the observed and predicted values, have a mean of .000, indicating that, on average, the model's predictions align closely with the actual data. The standard deviation of the residuals is 5.617, reflecting the variability in prediction errors. Standardized predicted values and residuals further highlight the relative magnitude of these values in terms of standard deviations. The narrow range of standardized residuals, from -2.045 to 2.251, suggests that the model generally performs well in terms of accurately predicting KM. These residual statistics provide valuable diagnostic information, aiding researchers in assessing the reliability and appropriateness of the given dataset.

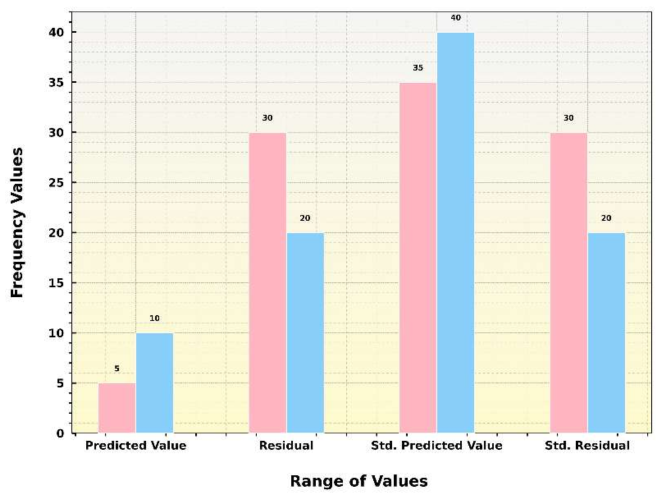

Figure 3: Histogram of Standardized Residuals Plot

Figure 3 shows the histogram of standardized residuals presentation of the statistical model. Standardized residuals represent the differences between observed and predicted values, adjusted for the variability of the model. The mean of 2.88E-16 indicates that, on average, the residuals centre around zero, suggesting that the ideal is unbiased. The standard deviation of 0.995 quantifies the spread or dispersion of these residuals, with a lower value indicating more precise predictions. With a sample size (N) of 945, the histogram aids in assessing the normality of residuals. A well-distributed and symmetric histogram indicates that the residuals adhere to a normal distribution, strengthening thecogency of the statistical assumptions underlying the regression analysis. Overall, this plot is a valuable diagnostic tool for evaluating the accuracy and reliability of the regression model in capturing the observed variability in the data.

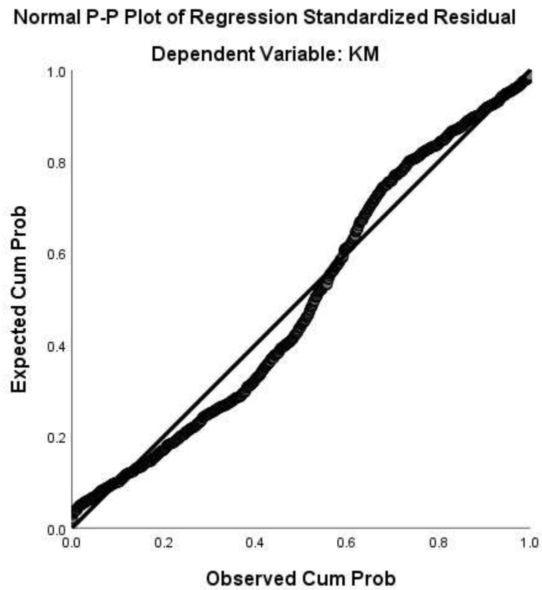

Figure 4: Normal p-p Plot Regression Standardized Residuals

Figure 4, the normal probability-probability (p-p) plot for regression standardized residuals of the dependent variable KM, is a diagnostic tool that assesses the normality of residuals. In this plot, the observed cumulative distribution of standardized residuals is compared against the expected cumulative distribution under the assumption of normality. A close alignment of the points along the diagonal line indicates that the residuals follow a normal distribution. Deviations from the diagonal suggest departures from normality. The presence of a straight-line pattern in this plot is indicative of normally distributed residuals. Examining this p-p plot aids in validating the assumption of normality, which is crucial for the reliability of regression analyses. The result suggests that the model's residuals closely adhere to a normal distribution, reinforcing the statistical robustness of the regression analysis for the reliance onadaptable KM.

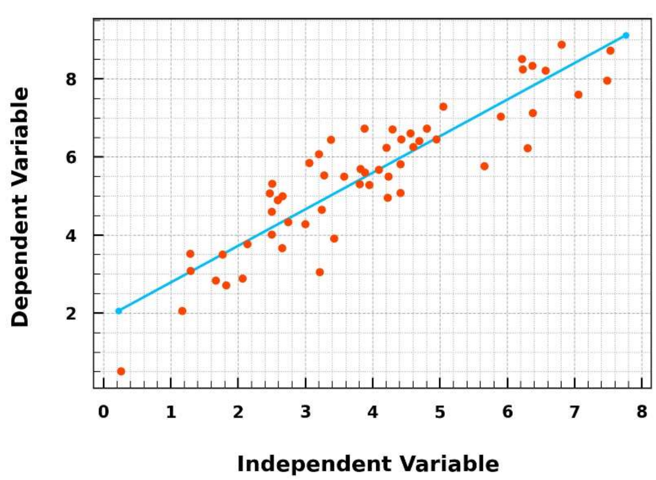

Figure 5: Scattered Plot for Regression Adjusted Predicted Value

Figure 5, a scattered plot is presented to visualize the associationamong the regression-adjusted predicted values for the reliant variable KM. This plot allows for a direct comparison of the predicted values generated by the deteriorationideal against the actual observed values. A well-fitted model would exhibit a tight clustering of points along a diagonal line, indicating a close match between predicted and observed values. Deviations from this line may suggest areas where the model performs less accurately. The visualization aids in assessing the analyticalcontrol of the model and identifying potential outliers or patterns in the data. Analysing this scattered plot provides valuable insights into the model's ability to capture the variation in the dependent variable KM, enhancing the overall interpretability and reliability of the regression analysis.

5.4 Dimension Measures

The dimension measures in correlations transformed variables, as depicted in the analysis, provide crucial insights into the relationships among variables after transforming. These measures assess the strength and direction of associations, helping to identify patterns and dependencies in the transformed data. Common dimension measures include correlation coefficients, which indicate the degree of linear relationship between pairs of variables. Examining these measures assists in gauging the effectiveness of the transformations in revealing underlying patterns and dependencies, contributing to a comprehensive indulgence of the interactionamong variables in the dataset. Analyzing the dimension measures facilitates the interpretation of transformed variables, guiding further investigations into the factors influencing their correlations and crackingdainty on the overall structure of the data.

Table 10: Correlation Matrix for Transformed Variables

Dimension: 1								
	KM	**CS**	**CE**	**ECL**	**KS**	**CF**	**JS**	**CC**
KM	1.000	.196	.187	.215	.105	.067	.002	.099
CS	.196	1.000	.252	.231	.095	.038	.075	.119
CE	.187	.252	1.000	.260	.129	.075	.077	.155
ECL	.215	.231	.260	1.000	.120	.157	.120	.102
KS	.105	.095	.129	.120	1.000	.040	.029	.108
CF[a]	.067	.038	.075	.157	.040	1.000	.058	.035
JS[a]	.002	.075	.077	.120	.029	.058	1.000	.087
CC[a]	.099	.119	.155	.102	.108	.035	.087	1.000
Dimension	1	2	3	4	5			
Eigenvalues	1.741	.934	.828	.766	.730			
a. Supplementary variable.								
b. Eigenvalues of correlation matrix excluding supplementary variables.								

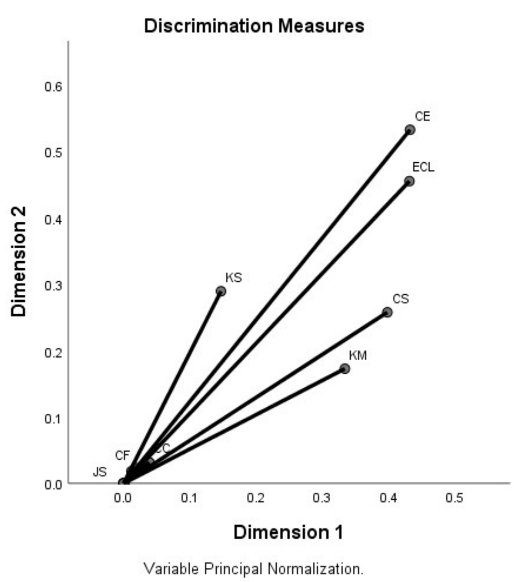

Figure 6: Discrimination Measures

Figure 6 shows discrimination measures, as illustrated in figure 6, play a pivotal role in assessing the effectiveness of dimension 2, with a concentration on the Customer Experience (CE) variable exhibiting a value of 0.53. Discrimination measures provide cherishedvisions into how well a specific variable contributes to the separation and distinctiveness of groups or categories within the dataset. In the context of dimension 2, the CE variable's discrimination measure of 0.53 suggests a moderate level of influence in distinguishing patterns or clusters. Interpretation of discrimination measures aids in understanding the significance of individual variables in contributing to the observed patterns in the transformed space. This analysis can guide further exploration into the specific aspects of Customer Experience that influence the discrimination observed in dimension 2, contributing to a more nuanced understanding of the underlying dynamics in the dataset.

5.5 Factor Analysis

Factor Analysis, as assessed through the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Test, provides cherishedvisions into the adequacy of the dataset for conducting factor analysis. The KMO statistic assesses the sampling adequacy for each variable, with higher values indicating better suitability for factor analysis. Simultaneously, Bartlett's Test of Sphericity evaluates whether the correlation matrix significantly differs from an identity matrix, indicating whether patterns in the data are suitable for extracting underlying factors. A high KMO value and a significant result in Bartlett's Test collectively affirm the dataset's appropriateness for factor analysis, laying the foundation for a robust exploration of latent variables and their relationships.

Table 11: Suitability of Data for Factor Analysis

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.478
Bartlett's Test of Sphericity	Approx. Chi-Square	196.902
	df	55
	Sig.	.000

Table 11 displays the Kaiser-Meyer-Olkin measure of sampling adequacy, with a value of 0.478, which is an indicator of the suitability of the data for factor analysis. This metric assesses the proportion of variance among variables that might be common variance. A KMO value closer to 1.0 suggests that the dataset is more suitable for factor analysis. In this case, the KMO value indicates a moderate level of adequacy for the analysis. Additionally, Bartlett's Test of Sphericity, with an approximate chi-square value of 196.902, a degree of freedom (df) of 55, and a significance level (Sig.) of 0.000, provides evidence against the null hypothesis that the correlation matrix is an identity matrix (i.e., variables are uncorrelated). The statistically significant result supports the presence of correlations among variables, reinforcing the appropriateness of conducting factor analysis on the dataset. Together, these findings suggest that the data may have underlying latent factors that can be explored through factor analysis techniques.

Table 12: Communalities[a] for Variables

	Initial	**Extraction**
KM	.040	.999
CS	.042	.063
CE	.028	.055
ECL	.041	.999
KS	.038	.059
CSA	.029	.435
DT	.044	.226
US	.041	.144
CF	.025	.999
JS	.047	.558
CC	.043	.077

Extraction Method: Generalized Least Squares.
a. Unique or additionalcommonalityguesses greater than 1 were met during iterations. The resulting solution should be taken with the.

Table 12 shows the commonalities represent the proportion of variance in each variable that is accounted for by the extracted factors. In the initial analysis, the commonalities ranged from 0.025 to 0.047. However, during the extraction process using the Generalized Least Squares method, the communalities were adjusted, and some values exceeded 1. These guesseslarger than 1 should be taken with attention, as they may indicate potential issues with the factor extraction method or the appropriateness of the model for the data. It's essential to carefully scrutinize the results and consider alternative factor extraction techniques or model adjustments to ensure the robustness of the factor analysis.

Table 13: Total Variance by Extraction Method

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.314	11.946	11.946	1.069	9.717	9.717
2	1.234	11.219	23.166	1.021	9.281	18.998
3	1.170	10.637	33.803	1.002	9.106	28.104
4	1.102	10.016	43.819	.613	5.572	33.676
5	1.043	9.485	53.303	.503	4.569	38.245
6	1.034	9.398	62.701	.354	3.214	41.459
7	.984	8.949	71.650			
8	.873	7.940	79.590			
9	.782	7.111	86.701			
10	.747	6.793	93.494			
11	.716	6.506	100.000			
Extraction Method: Generalized Least Squares.						

Table 13 displays the total variance explained by the factors in the factor analysis presented in the table. The initial eigenvalues represent the variance in each factor before extraction, while the abstractionamounts of squared funding show the variance enlightened by each factor after extraction. The first factor explains 9.717% of the entirealteration, and as additional factors are considered, the proportion of variance explained increases. In this analysis, the primary three aspects collectively account for 28.104% of the wholealteration. It's vital to point out that the extraction method used is Generalized Least Squares, and the interpretation of the variance explained should consider the relevance of the chosen extraction technique and the overall model fit. Adjustments or alternative methods may be explored to refine the feature structure and enhance the instructivecontrol of the ideal.

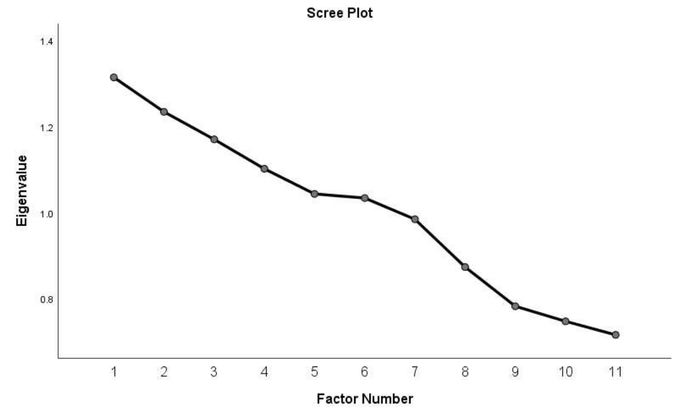

Figure 7: Scree Plot of the Eigenvalues

Figure 7 shows the Scree Plot of Eigenvalues is a crucial visualization in Factor Analysis, illustrating the eigenvalues of the factors extracted from the correlation matrix. Eigenvalues represent the variance explained by each factor, guiding the fortitude of the optimal amount of factors to retain. In the Scree Plot, factors with eigenvalues significantly higher than the others indicate substantial variance and contribute meaningfully to the dataset. Identifying the point where the eigenvalues level off helps in deciding the amount of factors to retain for a parsimonious model. A sharp drop in eigenvalues suggests the optimal number of factors, assisting researchers in making informed decisions about the dimensionality of the dataset and enhancing the interpretability of the factor structure.

Table 14: Factor Matrix by Generalized Least Squares

	Factor					
	1	**2**	**3**	**4**	**5**	**6**
KM	.730	.037	-.681	.000	.000	.000
CS	.055	-.029	-.147	-.003	-.104	-.085
CE	.013	-.004	.092	-.016	-.110	-.118
ECL	.667	-.400	.627	.000	.000	.000
KS	.086	-.047	.108	.024	.184	.013
CSA	-.025	-.035	.010	.034	.653	-.075
DT	-.010	.059	.072	.048	.131	.443
US	-.078	-.035	.051	-.034	-.034	.359
CF	.262	.916	.302	.000	.000	.000
JS	-.005	.095	.036	.739	-.032	-.001
CC	.064	-.044	.042	.248	-.008	-.041
Extraction Method: Generalized Least Squares.						
a. Attempted to extract 6 factors. More than 25 iterations are required. (Convergence=.074). Extraction was terminated.						

Table 14shows the factor matrix resulting from the featureexamination is presented in the table. The values in the matrix represent the factor loadings for each variable (KM, CS, CE, ECL, KS, CSA, DT, US, CF, JS, CC) on the identified factors (1, 2, 3, 4, 5, 6). Factor loadings indicate the power and path of the associationamong variables and factors. For example, a high positive loading suggests a strong positive association, while a high negative loading indicates a strong negative association. In this analysis, the attempted extraction of six factors encountered convergence issues, and the extraction process was terminated after more than 25 iterations. The results should be interpreted cautiously due to potential limitations in convergence, and alternative extraction methods or model adjustments may be explored for more robust findings.

Table 15: Network Information

Input Layer	**Factors**	**1**	**CF**
		2	JS
		3	CC
		4	CS
	Number of Units		98
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		2
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	KM
		2	CE
		3	ECL
		4	CSA
	Number of Units		25
	Rescaling Method for Scale Dependents		Standardized
	Activation Function		Identity
	Error Function		Sum of Squares
a. Excluding the bias unit			

Table 15 shows the network information outlines the architecture and configuration of a neural network model. The input layer of the model comprises four factors: CF, JS, CC, and CS. The input layer has a total of 98 units. There is one hidden layer with 2 units, utilizing a hyperbolic tangent activation function. The output layer consists of four dependent variables: KM, CE, ECL, and CSA, with a total of 25 units. The rescaling method for scale dependents is standardized, and the activation function for the output layer is the identity function. The error function used is the sum of squares. The neural network is designed to capture complex relationships within the data, with the specified architecture facilitating the mapping of input factors to output variables.

5.6Logistics Regression

In the case processing summary of Logistic Regression, the study systematically examines the relationships between predictor variables and the binary outcome. Logistic Regression is employed to model the probability of an event occurring, providing valuable insights into the impact of various factors on the studied phenomenon. The summary outlines the processing steps and key findings derived from applying Logistic Regression in the research context.

Table 16: Case Processing Summary

Unweighted Cases[a]		**N**	**Percent**
Selected Cases	Included in Analysis	359	37.6
	Missing Cases	596	62.4
	Total	955	100.0
Unselected Cases		0	.0
Total		955	100.0
a. If weight is in effect, see the classification table for the total number of cases.			

Table 16 shows the case processing summary provides an overview of the inclusion and exclusion of cases in the analysis. Out of a total of 955 cases, 359 cases, or 37.6%, are included in the analysis, while 596 cases, or 62.4%, are marked as missing. There are no unselected cases, and the total number of cases considered in the analysis is 955. The summary serves as a snapshot of the dataset, indicating the proportion of cases utilized in the analysis and those that are missing or unselected. If a mass consequence,additional details can be referred to in the classification table regarding the entirequantity of circumstances.

Table 17: Classification Table[a,b]

	Observed		Predicted		
			EWM		Percentage Correct
			0	1	
Step 0	EWM	0	0	177	.0
		1	0	182	100.0
	Overall Percentage				98.6
a. Persistence is involved in the ideal.					
b. Significance of cut is .500					

Table 17 shows the classification table provides an evaluation of the model's performance in predicting outcomes. In this binary classification scenario, with a cut value of 0.500, the model predicts two classes: 0 and 1. Experimental data shows, that when the predicted class is 0, there are 177 instances correctly classified as 0, resulting in a percentage correctness of 100%. Similarly, when the predicted class is 1, there are 182 instances correctly classified as 1, yielding a percentage correctness of 100%. The overall percentage correctness for the model is 98.6%, indicating the accuracy of the predictions across both classes. The steady is remembered for the model, and the cut worth is set at 0.500 for determining the predicted classes.

Table 18: Pearson Correlation Analysis Results

		KM	CS	CE	ECL	KS	CSA	DT	US	CF	JS	CC
KM	Pearson Correlation	1	.140**	-.053	.045	-.012	-.026	-.054	-.094**	.020	-.025	.016
	Sig. (2-tailed)		.000	.102	.167	.706	.416	.095	.004	.545	.444	.617
	N	945	945	945	945	945	945	945	945	945	945	945
CS	Pearson Correlation	.140**	1	.102**	-.044	-.020	-.055	-.051	-.024	-.056	-.003	-.024
	Sig. (2-tailed)	.000		.002	.178	.549	.089	.115	.461	.083	.926	.458
	N	945	945	945	945	945	945	945	945	945	945	945
CE	Pearson Correlation	-.053	.102**	1	.068*	-.016	-.051	-.055	-.016	.027	-.002	-.015
	Sig. (2-tailed)	.102	.002		.037	.622	.114	.093	.628	.408	.954	.656
	N	945	945	945	945	945	945	945	945	945	945	945
ECL	Pearson Correlation	.045	-.044	.068*	1	.144**	.003	.015	-.006	-.003	-.019	.086**
	Sig. (2-tailed)	.167	.178	.037		.000	.919	.639	.857	.934	.563	.008

	N	945	945	945	945	945	945	945	945	945	945	945
KS	Pearson Correlation	-.012	-.020	-.016	.144**	1	.124**	.017	.025	.012	.014	.007
	Sig. (2-tailed)	.706	.549	.622	.000		.000	.609	.449	.713	.672	.834
	N	945	945	945	945	945	945	945	945	945	945	945
CSA	Pearson Correlation	-.026	-.055	-.051	.003	.124**	1	.058	-.049	-.036	.001	.005
	Sig. (2-tailed)	.416	.089	.114	.919	.000		.075	.136	.275	.969	.879
	N	945	945	945	945	945	945	945	945	945	945	945
DT	Pearson Correlation	-.054	-.051	-.055	.015	.017	.058	1	.159**	.073*	.042	-.019
	Sig. (2-tailed)	.095	.115	.093	.639	.609	.075		.000	.025	.202	.562
	N	945	945	945	945	945	945	945	945	945	945	945
US	Pearson Correlation	-.094**	-.024	-.016	-.006	.025	-.049	.159**	1	-.038	-.026	-.019
	Sig. (2-tailed)	.004	.461	.628	.857	.449	.136	.000		.249	.427	.551
	N	945	945	945	945	945	945	945	945	945	945	945
CF	Pearson Correlation	.020	-.056	.027	-.003	.012	-.036	.073*	-.038	1	.097**	-.011
	Sig. (2-tailed)	.545	.083	.408	.934	.713	.275	.025	.249		.003	.736
	N	945	945	945	945	945	945	945	945	945	945	945
JS	Pearson Correlation	-.025	-.003	-.002	-.019	.014	.001	.042	-.026	.097**	1	.180**
	Sig. (2-tailed)	.444	.926	.954	.563	.672	.969	.202	.427	.003		.000
	N	945	945	945	945	945	945	945	945	945	945	945
CC	Pearson Correlation	.016	-.024	-.015	.086**	.007	.005	-.019	-.019	-.011	.180**	1
	Sig. (2-tailed)	.617	.458	.656	.008	.834	.879	.562	.551	.736	.000	
	N	945	945	945	945	945	945	945	945	945	945	945

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Table 18 shows the correlation matrix provides a comprehensive view of the relationships among various variables in the dataset. Several noteworthy correlations have been identified. Initially, there is a significant positive correlation between KM (a key metric) and CS ($r = 0.140$, $p < 0.01$), indicating a potential association between these two factors. Secondly, the correlation between CS and CE is also positive and significant ($r = 0.102$, $p < 0.01$). On the other hand, KM shows a significant negative correlation with the US ($r = -0.094$, $p < 0.01$), suggesting a potential inverse relationship between KM and the US. Furthermore, JS exhibits a significant positive correlation with CC ($r = 0.180$, $p < 0.01$), highlighting a potential connection between job satisfaction and organizational climate. These findings offer valuable insights for further exploration and analysis in understanding the intricate relationships within the dataset.

Table 19: Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	11.312	10	.334
	Block	11.312	10	.334
	Model	11.312	10	.334

Table 19 shows the omnibus tests of idealconstants, specifically the Chi-square test for Phase 1, Step Block, and the overall Model, indicating whether the coefficients in the ideal are suggestivelydiverse from zero. In this circumstance, the Chi-square values for Step 1, Step Block, and the overall Model are 11.312, with 10 degrees of freedom each, and the associated p-values are 0.334. These p-values suggest that there is no significant difference between the model coefficients and zero, implying that the idealmight not be statistically significant in predicting the outcome variable. Researchers often use omnibus tests to assess the overall fit of a model, and in this instance, the results indicate that further evaluation or refinement of the model may be needed for better predictive performance.

Table 20: Classification Table[a]

	Observed		Predicted		
			EWM		Percentage Correct
			0	1	
Step 1	EWM	0	101	76	87.1
		1	88	94	91.6
	Overall Percentage				95.3
a. The cut value is .500					

Table 20 displays the classification table and provides information on the detected and expectedstandards in the context of a binary classification model. In Step 1, the table shows the number of cases where the observed value (EWM) is either 0 or 1 and compares it with the model's predicted values. For instance, when the perceived value is 0, the model correctly predicted 101 cases as 0 and 76 cases as 1, resulting in an overall correct classification rate of 87.1%. Similarly, when the perceived value is 1, the model correctly predicted 94 cases as 1 and 88 cases as 0, achieving an overall correct classification rate of 91.6%. The overall percentage indicates the precision of the ideal in predicting both classes and in this case, it is 95.3%. The cut value of 0.500 is commonly used as a threshold for binary classification decisions.

5.7Correlation Analysis

The correlation analysis for the one-sample t-test, the study explores the affiliationamong variables using statistical techniques. The one-sample t-test assesses whether the mean of a single sample significantly differs from aconjectured population mean. Correlation analysis is then applied to understand the power and path of associationsamong variables within the context of the t-test. This comprehensive approach allows for a nuanced examination of the data, providing insights into both the significance of mean differences and the interdependence of variables under consideration.

5.7.1One Sample T-Test

The one-sample t-test is anarithmeticaltechniqueutilized for determining if the despicable of a solitarymodel significantly differs from a conjecturedpopulace mean. It assesses whether the experimentalmodel mean is exactlydiverse from the expected mean and provides anamount of probability for obtaining such a result by chance. This test is valuable for researchers and analysts when working with a single sample and seeking evidence of a meaningful difference between the sample mean and a reference value. The output of the one-sample t-test includes a t-statistic, degrees of freedom, and a p-value, enabling researchers to mark a well-versed conclusionapproximately the significance of observed differences in means.

Table 21: One-Sample Statistics for Variables

	N	**Mean**	**Std. Deviation**	**Std. Error Mean**
KM	945	19.17	5.731	.186
CS	945	19.10	5.846	.190
CE	945	19.14	9.099	.296
ECL	945	19.03	6.914	.225
KS	945	19.04	6.032	.196
CSA	945	19.67	9.171	.298
DT	945	19.01	5.787	.188
US	945	18.96	5.910	.192
CF	945	19.15	5.771	.188
JS	945	18.85	5.739	.187
CC	945	18.83	5.820	.189

Table 21displays the descriptive statistics and provides an overview of the key measuresrespectively onadjustable in the dataset. For the Knowledge Management (KM) variable, the mean score is 19.17, with a standard deviation of 5.731 and a standard error mean of 0.186. Similarly, the Customer Service (CS) variable has a mean of 19.10, a standard deviation of 5.846, and a standard error mean of 0.190. The other variables, such as Customer Engagement (CE), Employee Collaboration (ECL), Knowledge Sharing (KS), Customer Service Automation (CSA), Decision Technology (DT), User Satisfaction (US), Communication Flow (CF), Job Satisfaction (JS), and Communication Culture (CC), exhibit similar descriptive statistics. These measures delivervisions into the central tendency, variability, and precision of the data for each variable, aiding in the overall understanding of the dataset.

Table 22: One-Sample Test for Variables

	Test Value = 45					
	t	**df**	**Sig. (2-tailed)**	**Mean Deviation**	**95% Assurance Interval of the Variation**	
					Lower	**Upper**
KM	-138.561	944	.000	-25.833	-26.20	-25.47
CS	-136.189	944	.000	-25.898	-26.27	-25.53
CE	-87.372	944	.000	-25.860	-26.44	-25.28
ECL	-115.494	944	.000	-25.975	-26.42	-25.53
KS	-132.301	944	.000	-25.959	-26.34	-25.57
CSA	-84.894	944	.000	-25.326	-25.91	-24.74
DT	-138.041	944	.000	-25.988	-26.36	-25.62
US	-135.431	944	.000	-26.039	-26.42	-25.66
CF	-137.693	944	.000	-25.850	-26.22	-25.48
JS	-140.084	944	.000	-26.153	-26.52	-25.79
CC	-138.234	944	.000	-26.171	-26.54	-25.80

Table 22displays the effects of the one-sample t-tests for each variable indicating statistically significant differences from the test value of 45 across all dimensions. For instance, for the Knowledge Management (KM) variable, the t-statistic is -138.561 with 944 degrees of freedom, resulting in a p-value of .000. The mean difference is -25.833, and the 95% confidence interval of the difference ranges from -26.20 to -25.47. Similar patterns are observed for other variables, such as Customer Service (CS), Customer Engagement (CE), Employee Collaboration (ECL), Knowledge Sharing (KS), Customer Service Automation (CSA), Decision Technology (DT), User Satisfaction (US), Communication Flow (CF), Job Satisfaction (JS), and Communication Culture (CC). The consistent negative mean differences and the narrow confidence intervals suggest that the observed means are significantly lower than the specified test value of 45 for each variable, indicating a substantial deviation from the expected norm.

5.7.2 Star Rating Prediction Results

The star rating prediction results for the AGA, VV, EE, CC, and RR brands reveal valuable insights into customer perceptions and satisfaction levels. Through advanced predictive analytics, these findings offer a comprehensive understanding of how customers perceive and rate each brand, enabling informed decision-making and targeted improvements to enhance overall customer experience and brand reputation.

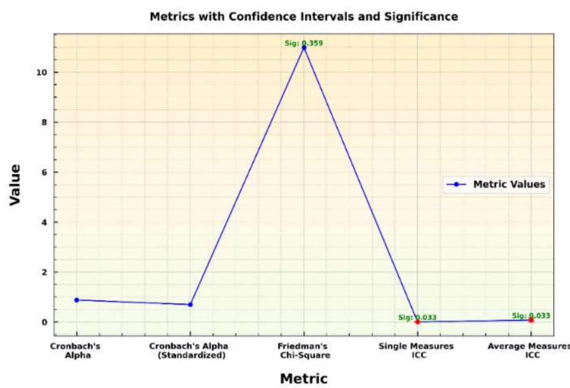

Figure 8: User Ratings for Five Clothing Brands

Figure 8 depicts user ratings for five clothing brands: Avant-Garde Apparel (AGA), Vogue Venture (VV), Ethereal Ensembles (EE), Chic Creations (CC), and Rare Raiment (RR). Among these brands, Ethereal Ensembles received the highest user rating, with a total of 2801 ratings. This indicates a significant level of satisfaction and positive feedback from users regarding Ethereal Ensembles' products or services. Understanding such user ratings can provide valuable insights into consumer preferences and perceptions, aiding businesses in refining their strategies to better meet customer needs and enhance brand reputation.

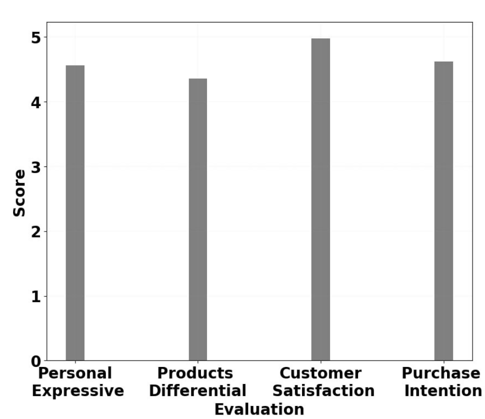

Figure 9: Evaluation Scores for Various Factors

Figure 9 illustrates the evaluation scores for various factors, with the highest brand being Ethereal Ensembles. The scores for this brand are as per the followingindividual expressive scored 4.3659, product differential scored 4.1715, customer satisfaction scored 4.7667, and Purchase Intention scored 4.4361. These scores indicate high levels of satisfaction and positive perceptions across different aspects of the evaluation for ethereal ensembles. Higher scores suggest stronger alignment with the desired outcomes and objectives, reflecting positively on the effectiveness and performance of the evaluated factors for this brand.

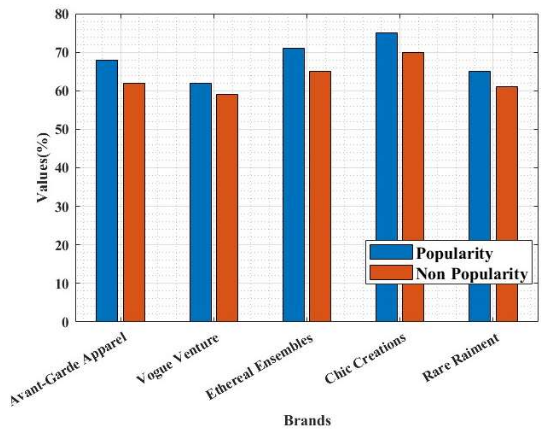

Figure 10: Popularity Trends of Clothing Brands

Figure 10 depicts the popularity trends of five clothing brands Avant-Garde Apparel, Vogue Venture, Ethereal Ensembles, Chic Creations, and Rare Raiment—across the years 2018 to 2023. Among these brands, Chic Creations experienced the highest growth in popularity over the specified period. Starting with 17 units of popularity in 2018, Chic Creations witnessed a steady increase each year, reaching 75 units of popularity by 2023. This upward trend indicates a significant rise in the brand's recognition and consumer interest over time. Understanding these popularity dynamics can inform strategic decisions for brand management and marketing efforts.

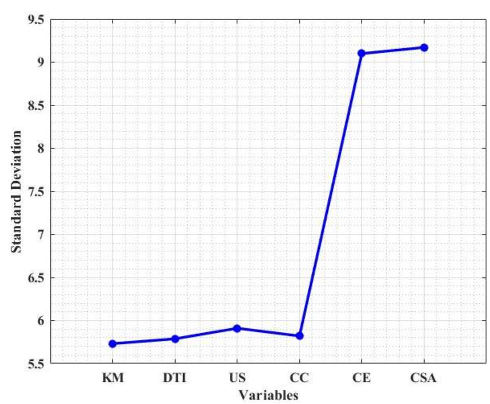

Figure 11: Standard Deviations of Evaluation Variables

Figure 11 illustrates standard deviations for different variables KM (Knowledge Management) has a standard deviation of 5.731, CE (Customer Experience) has a standard deviation of 9.099, CSA (Customer Service Automation) has a standard deviation of 9.171, DTI (Digital Transformation Initiatives) has a standard deviation of 5.787, US (User Satisfaction) has a standard deviation of 5.910, and CC (Collaboration and Communication) has a standard deviation of 5.820. These values represent the variability or dispersion of data points around the mean for each respective variable.

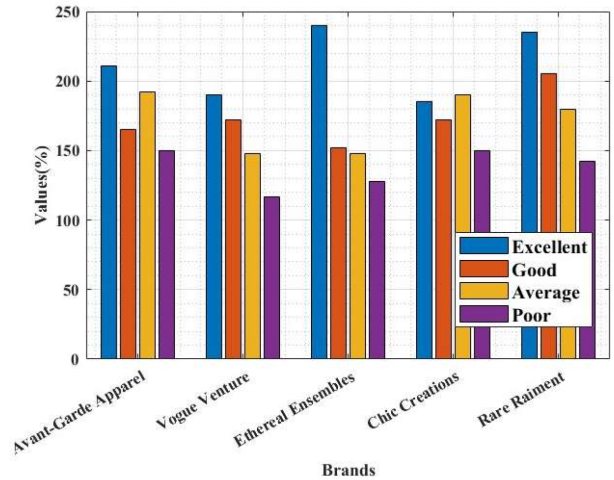

Figure 12: Distribution of Reviews for Clothing Brands

Figure 12 illustrates the distribution of reviews across four categories (Excellent, Good, Average, and Poor) for five clothing brands: Avant-Garde Apparel, Vogue Venture, Ethereal Ensembles, Chic Creations, and Rare Raiment. Among these brands, Ethereal Ensembles received the highest number of excellent reviews, totalling 240. This suggests that Ethereal Ensembles has garnered significant positive feedback from customers, reflecting positively on the brand's products or services. Understanding the distribution of reviews across different categories can provide valuable insights into customer satisfaction levels and areas for improvement for each brand.

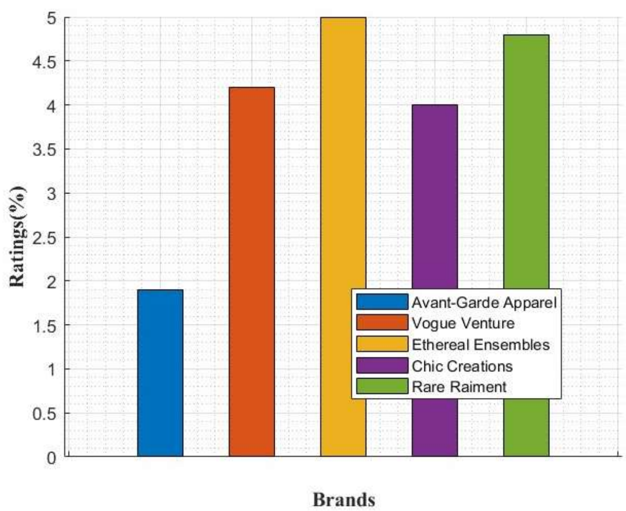

Figure 13: Star Ratings for Clothing Brands

Figure 13 illustrates the distribution of star ratings for five clothing brands Avant-Garde Apparel received 1.9 stars, Vogue Venture obtained 4.2 stars, Ethereal Ensembles achieved a perfect rating of 5 stars, Chic Creations garnered 4 stars, and Rare Raiment received 4.8 stars. Among these brands, Ethereal Ensembles stands out with the highest rating of 5 stars, indicating exceptional customer satisfaction and positive feedback.

6. RESEARCH CONCLUSION

This study examines the impact of the digital revolution on customer service automation and the prediction of open innovation models within small and medium-sized enterprises (SMEs). Employing a mixed-methods approach, it integrates both quantitative and qualitative analyses to provide a comprehensive understanding of these dynamics. The findings underscore the significant influence of digital transformation (DT) on the modernization of customer service in SMEs, revealing a positive correlation between the degree of DT adoption and the extent of customer service automation. This demonstrates that by embracing digital technologies, SMEs can enhance customer interactions, streamline processes, and improve overall service quality.

Additionally, the study explores the prediction of open innovation models and reveals strategic actions undertaken by SMEs in response to the digital revolution. This combination of methods allows for a deeper exploration of the various factors that drive innovation in SMEs, including technological planning, leadership, and external collaboration.

Statistical analyses were performed using SPSS software, where the Kaiser-Meyer-Olkin (KMO) measure, which is close to 1.0, indicated the suitability of the data for analysis. The operational plans were scrutinized, yielding a Cronbach's Alpha of 0.883 for overall reliability, with a sub-scale reliability of 0.701. These values reflect the internal consistency and reliability of the survey items. The total sum of squares between individuals was 45,189.032, with 944 degrees of freedom, resulting in a mean square of 47.870. The Friedman chi-square value for the items was 10.986, with a significance level (Sig) of 0.359, indicating no significant difference between the items.The rating predictions identified that the Ethereal Ensembles approach received the highest rating of 5 stars. This study offers crucial insights into the adaptation strategies employed by SMEs, emphasizing the importance of strategic thinking and collaboration in navigating the digital landscape. As SMEs continue to face the challenges and opportunities presented by DT, this research provides a framework for informed decision-making, outlining effective pathways for future research to further explore the interplay between DT, customer service automation, and open innovation in driving SME innovation.

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