PLS-SEM Approach and Sentiment Analysis for Identifying Significant Factors of Customer Satisfaction

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***Abstract*—Reviews have a direct impact on customer satisfaction. The aim of this study is to dissect and analyze a collection of 775 negative and 557 positive comment reviews, drawn from four distinct e-commerce platforms. By classifying these remarks into positive and negative sentiments, this research endeavors to illuminate underlying trends permeating these marketplaces. The research methodology employed involves field observations of online shopping experiences, utilizing data derived from 254 e-commerce customers. These data were collected via validated questionnaires and subsequently analyzed using the partial least squares structural equation modeling approach, employing the lavaan r library within the R programming environment. The questionnaire results produced a rating scale from 1 to 5, categorizing responses from "very satisfied" to "less satisfied", effectively illustrating both positive and negative commentary. The field comment data collected was coordinated with comment data extracted from four marketplace trading accounts. This data comment customer was analyzed using a range of comparative models such as k-nearest neighbors, multinomial naive bayes , stochastic gradient descent , and decision trees to conduct sentiment analysis. The findings reveal that the naive bayes method generates the greatest accuracy in sentiment analysis, registering an accuracy value of 0.886. Moreover, the analysis executed through r programming indicates that the e-service quality model yields the most robust results, reflected by an adjusted r-square value of 0.885. This study exerts a notable impact on service quality, as evidenced by a coefficient value of 0.865 and a perceived reputation score of 0.162.**

Keywords—e-commerce, sentiment analysis, product reviews, r programming.

I. INTRODUCTION

In recent years, e-commerce and online shopping platforms have witnessed a substantial surge in popularity, culminating in robust brand images and favorable product reviews. This trend is projected to persist as an increasing number of consumers choose the comfort and convenience of online shopping. Consequently, e-commerce companies have become progressively dependent on product recommendation systems. These systems tailor the shopping experience to the individual tastes and interactions of each user with the platform. Such personalized recommendation systems have emerged as essential instruments driving the success of online retail businesses [1].

A vital facet of these systems is the accumulation of user feedback through reviews. As users participate in the reading and composing of reviews, they can glean valuable insights from their peers, which in turn facilitates more informed purchasing decisions. Platforms that underscore the importance of nurturing social relationships and promoting user-generated opinions are identified as social recommendation systems.[2].

Recent studies have illuminated the concept that a positive experience is cultivated when perceived benefits outweigh the associated costs. This occurs when an individual's perception of a product or service surpasses their initial expectations, leading to a favorable disposition. Such feelings profoundly shape ensuing actions, including making a purchase, engaging in repeat business, or advocating the experience to others [3]. Social media platforms, serving as promotional avenues, hold substantial influence over customers' purchase intentions. The instantaneous and diverse features of social commerce platforms enable personalized engagements and collaborations, thereby augmenting consumer trust. This enhancement of trust is realized by delivering value as perceived by the customers [4]. The amalgamation of e-commerce and social media substantially influences customer purchasing choices, notably through the integration of e-commerce product assessments [5].

Prior studies have scrutinized customer reviews shared in text form on digital platforms, spanning statuses, tweets, comments, and evaluations. Key evaluation metrics employed encompass likability, helpfulness, and satisfaction. machine learning algorithms, including logistic regression , random forest, decision tree , k-nearest neighbor, support vector machine, multinomial naive bayes , stochastic gradient descent , and boost, have been utilized, in conjunction with the term frequency-inverse document frequency and bag-of-words features [6]. However, actual field observations related to consumer needs are seldom conducted, underscoring the importance of this research to uncover facts based on on-the-ground insights and marketplace commentary data. partial least squares-structural equation modeling) technique was utilized to delve deeper into the role of trust in the nexus between consumer social media engagement and customer satisfaction [7].

The results indicated that a heightened level of trust in online retailers promotes an increase in consumers' purchasing intentions and future repurchasing intentions by mitigating perceived risk [7]. Conversely, customer satisfaction can be described as the emotional reaction consumers have when comparing the perceived performance of products and services against their initial expectations. Such a comparison may engender sentiments of delight or frustration, contingent upon the standards set by previous experiences [8].

Within the realm of e-commerce, the security of websites is a paramount concern [9]. Hence, it becomes essential to conduct a survey to identify which cyber threat intelligence indicators could potentially impact customer satisfaction. Earlier research stood out as some of the first to explore the challenges posed by social commerce for entrepreneurs. The findings reveal that social media activity positively influences trust. In moments of uncertainty, consumers often resort to social media platforms to seek guidance and solutions. As per previous studies, social media stands as a pivotal element in shaping trust [10].

Concerning the efficacy of reviews, it was discovered that specific negative emotions, particularly those associated with the product experience, exerted a powerful influence on consumers' perceptions of the reviews [12]. Online reviews have ascended in their importance, and they are now seen as reliable resources on which consumers depend when making purchases [12]. The perceived usefulness of the reviews as a whole, and the individual product ratings within them, have been found to correlate with the quality of the information they contain [13].

II. RELATED WORK

Prior research has employed the smart pls tool to test the contextual model using partial least squares structural squation modeling . This current study builds upon that previous research, employing the pls-sem method to investigate reputation perception indicators that impact consumer satisfaction. These indicators include rapid delivery, swift complaint resolution, prompt responses to refund or exchange requests, and courteous behavior during refunds or exchanges. However, sentiment analysis was not incorporated into this study [3]. This study is predicated on prior research that investigated trust indicators in conjunction with service characteristic factors, fundamental service expectations, personalized service expectations, and social attributes. The novelty of this research lies in the validation of user comments directly, by comparing product comment data obtained through the seller's account at the e-commerce company [4]. This study builds upon previous research that employed the pls-sem method to evaluate service quality indicators that influence trust [24]. Several factors, including assurance, empathy, tangibility, responsiveness, and trustworthiness, were validated against product commentary data sourced from e-commerce companies [21] .In preceding studies, the naive bayes classifier was utilized to dissect consumer sentiment, whereas the support vector maching was employed to categorize user sentiment in binary terms. Data preprocessing techniques, such as term frequency and inverse document frequency , were implemented prior to feeding the data into the network model for feature assessment. The goal of this research was to ascertain a statistically superior machine learning methodology between the support vector maching and naive bayes classifiers [9].

Initially, this study employed the naive bayes classifier to analyze consumer sentiment, while the support vector maching was used to dichotomize user sentiment. The data underwent preprocessing using term frequency and inverse document frequency techniques, subsequently assessed by a network model for feature evaluation. The objective of this research was to discern a statistically superior machine learning methodology between the support vector maching and naive vayes classifiers [14]. In the domain of platform analysis, prior research scrutinized the characteristics of over 1.2 million reviews, penned by more than 327,000 users on the yelp bay area platform and amazon. The findings revealed that a compact group primarily composed the user reviews, and the most potent predictor of review success was the author's historical track record [6].

TABLE I. QUESTION FOR RESPONDENTS

Perceived Reputation [3]	E-Service Quality [21]	E-Trust [4]
(Fast delivery) Is the delivery of goods on e-commerce delivered quickly?	**(Assurance)** Is there a guarantee regarding damaged, defective, and rejected item that does not meet expectations?	**(Service characteristic)** Does e-commerce have service characteristics for service facilities for complaints of defective or inappropriate goods and service facilities for returning goods or money?
(Handling complaint fast) Are product and service customer complaints handled quickly using a trouble ticket or customer service?	**(Empathy)** Does the delivery party or the seller's account company in e-commerce have empathy when the item is damaged during purchase?	**(Basic service)** Is the basic service used in accordance with problem-solving using service level guarantee method?
(Fast answering for refund or change) Are customer complaints regarding refunds and changes to e-commerce accounts answered quickly?	**(Tangible)** Does the item order match customer's expectations after receiving product?	**(Personalised service)** Does E-Commerce personalize service based on categories such as the top ten high class customer?
(Friendly when refund or change) Do e-commerce sellers behave in a friendly manner when refunding or changing product pick-ups?	**(Responsive)** Is there customer service complaint service that is very responsive in solving problems?	**(Social attributes)** Do social media product reviews o affect the brand image of e-commerce sellers?
	(Reliability) Does any customer service have the reliability of troubleshooting to determine damaged or defective items?	

From Table I, presents a summary of the inquiries posed during direct observation, facilitated through the administration of questionnaires to customers.

III. METHODOLOGY

This study adopted methods from previous research but incorporated a distinct sentiment analysis algorithm. The initial stage involved the use of a questionnaire to gather direct feedback and recommendations from customers [15].

The subsequent stage comprised the collection of product comment data from seller accounts on e-commerce platforms such as tokopedia, shopee, lazada, and bukalapak. The final stage entailed the creation of a dashboard to monitor trends in negative and positive comments, as they relate to consumer product reviews on marketplace seller accounts. The fourth stage involves examining the accuracy of sentiment analysis results using algorithms such as k-nearest neighbors, multinomial naive bayes, stochastic gradient descent, and decision tree. This is accomplished by observing variations in analysis outcomes based on the accuracy of the sentiment analysis algorithm model. Figure 1 Flowchart methodology describes the flow of the research process

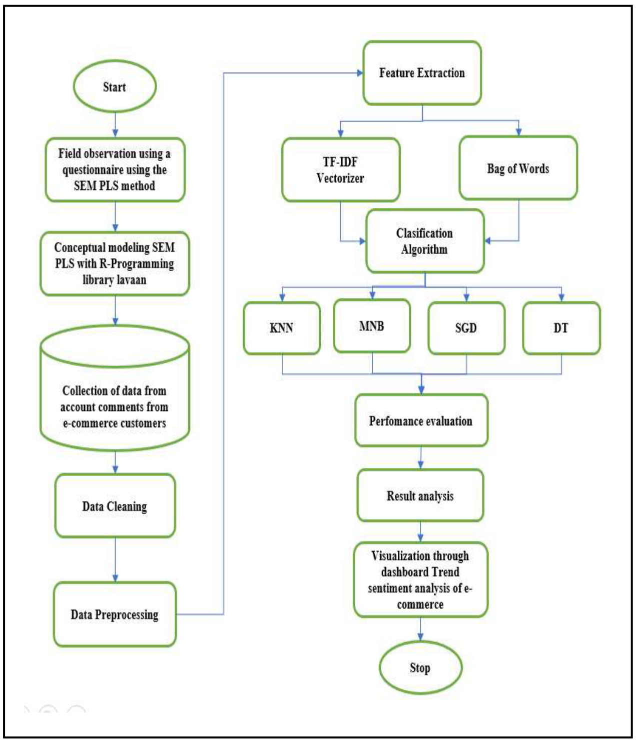

Fig. 1. Flowchart methodology.

A. Step 1 field observation with a questionnaire

Partial least squares structural equation modeling is a potent technique for causal modeling that seeks to maximize the variance explained by latent dependent variables using the predictors under investigation. A critical preliminary step involves crafting a diagram that depicts the interrelationships among the variables and delineates the research hypothesis. Path diagrams are utilized to graphically illustrate the theoretical and logical linkages between variables, acting as a visual representation of the hypothesis under test. The initial construction of these pathway models enables effective and visual organization of ideas, thereby facilitating a thorough examination of the interconnectedness among variables [16]. Hence, it's crucial to gather suggestions and feedback from customers regarding the seller's account in the marketplace. This information is then processed using the pls-sem method, modeled in the r programming language with the aid of the 'lavaan' library.

B. Step 2 retrieve data from the top ten seller accounts of the e-commerce company

After identifying keywords from the questionnaire results via the pls-sem method, sentiment classification was conducted to assign sentiment labels [23]. Performing large-scale sentiment analysis on user evaluations within e-commerce platforms holds the potential to elevate user satisfaction [16]. The dataset employed in this research incorporated both positive and negative feedback from seller accounts across various e-commerce platforms, specifically tokopedia, shopee, lazada, and bukalapak.

C. Step 3 classification of customer comment trends four e-commerce companies

The subsequent phase entailed analyzing customer comment trends based on their purchasing experiences to pinpoint the most prevalent negative and positive feedback from seller accounts at the four e-commerce companies. A trend dashboard, visualizing these positive and negative comments, was created using google collab. However, the distinctive aspect of this process was the exclusion of the pls-sem method as a direct field observation tool for consumer product reviews [17].

D. Step 4 comparison of the most precise models

In this phase, the accuracy of various models, namely k-nearest neighbors, multinomial naive bayes, stochastic gradient descent, and decision tree, were evaluated to identify the model with the highest accuracy.

IV. Experimental Result

A. Analysis of the model's overall quality with pls-sem

Partial least squares-structural equation modeling, is often considered exploratory in nature [22]. This analysis not only shares conceptual and practical similarities with multiple linear regression analysis in its aim to maximize the explained variance of the dependent variable, but it also extends this by including an assessment of the measurement model's quality. According to preliminary studies, pls-sem retains an exploratory characteristic [18].

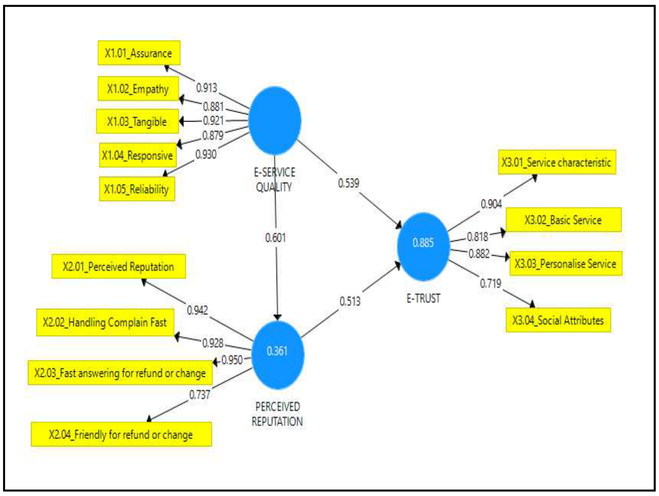

Fig. 2. Theory conceptual model.

Fig. 2 presents the survey results obtained using the smart pls application, a component-based technique chosen to evaluate the structural model [19]. This application was selected due to its capacity to manage both formative and reflective constructs, with minimal requirements on the sample size and residual distributions [20].

V. Evaluation

A. Analysis of structural equation modeling with library package lavaan use r programming

The lavaan module is a powerful open-source tool in r designed to support the analysis of multivariate models, including path analysis, confirmatory factor analysis, and structural equation modeling The name "lavaan" itself reflects its primary objective, which is to equip researchers with comprehensive tools for investigating, estimating, and comprehending diverse latent variable models. These models encompass a broad spectrum of techniques, such as factor analysis, structural equations, longitudinal analysis, stratified analysis, latent class analysis, item response theory, and methods for handling missing data.

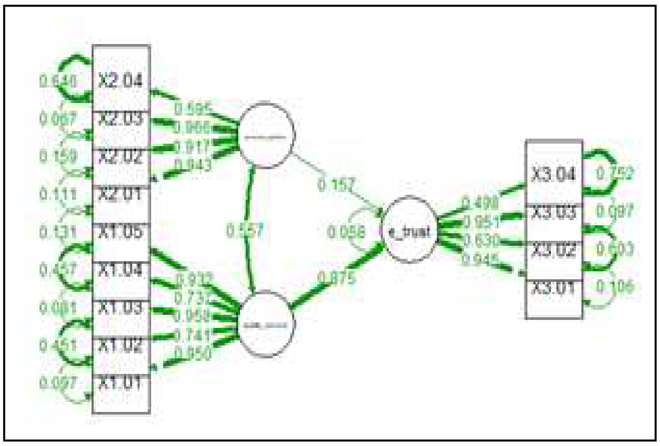

Fig. 3. Model SEM PLS in library lavaan use r programming.

Fig. 3 describe the pls-sem model, implemented in the lavalan library, effectively illustrates the relationships between variables at a significant level of 0.05. This implementation, conducted using the r programming language, is visually presented. The study's innovation lies in the validation of the sample model using r programming, alongside the creation of a sentiment analysis dashboard for comparing results.

TABLE II. Cross Loading Value and R Square

Indicator	Cronbach alpha (>0.7)	rho_a (>0.7)	Composite reliability (>0.7)	Average Variance (>0.5)	R Square Adjusted
E-Service Quality	0.945	0.948	0.958	0,819	0.885
Perceived Reputation	0.851	0.863	0.901	0.695	0.858
E-Trust	0.912	0.918	0.940	0.799	0.751

From Table II, describe the findings presented highlight a noteworthy observation: among the examined weights, only those in the pls-sem model demonstrate alignment with the concept of composite reliability, also referred to as rho_a. This measure of composite reliability provides insights into the scale's dependency by gauging the extent to which factors contribute to variance within the composite. In contrast, cronbach's alpha evaluates the internal consistency and interrelationships among items within a scale, offering a distinct perspective on the scale's reliability and interconnectedness.

Composite reliability is calculated by averaging the squared differences between each data point and the mean, providing a measure of the variance. This variance represents the total variance of the composite. On the other hand, adjusted r-squared, a modified version of r-squared, takes into account the number of predictors employed in the model. By considering the number of predictors, adjusted R-squared provides a more accurate evaluation of the model's explanatory power. The adjusted R-squared takes into account the relative contribution of predictors by dividing the total variance by the variance of factors, while also considering the number of predictors involved. This adjustment enables a more accurate assessment of the model's explanatory power, accounting for the complexity and number of predictors utilized.

The r-squared (R2) value serves as a measure of scale dependence, indicating the degree to which the variation in exogenous variables can be accounted for by one or multiple factors. R2 values greater than 0.75 are generally regarded as significant, while values between 0.50 and 0.75 suggest moderate significance. On the other hand, values below 0.25 are considered weak or insignificant. Evaluating the R Square results presented above, it is evident that the value of 0.885 exceeds the threshold of 0.75, indicating a substantial level of significance. Hence, the e-service quality indicator demonstrates a significant impact, as indicated by its high value of 0.885. Moreover, the e-service quality indicator (0.945), perceived reputation (0.851), and e-trust (0.912) values surpass the accepted threshold of 0.7 for Cronbach's alpha, signifying excellent reliability for the questionnaire items. For each indicator, the composite reliability (rho_a) value surpasses the 0.7 threshold, further affirming the goodness of the model.

TABLE III. The Model Fit Summary

	Saturated model	Estimated model
SRMR	0.125	0.125
d_ULS	1.430	1.430
d_G	2.122	2.122
Chi-Square	2085,736	2085,736
NFI	0.600	0.600
Rms Theta	0,360	0,360

From Table III, describe the model's adequacy was assessed using the results presented,, which includes ther mean square theta (rms theta) value of 0.360, accompanied by a standard deviation of 0.102. These values serve as crucial criteria for evaluating the fit of the model.

```
Latent Variables:
                      Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  quality_service =~
    X1.01                1.000                               0.873    0.950
    X1.02                0.666    0.041   16.257    0.000    0.581    0.741
    X1.03                1.014    0.029   34.891    0.000    0.886    0.958
    X1.04                0.681    0.042   16.072    0.000    0.595    0.737
    X1.05                0.999    0.033   30.591    0.000    0.873    0.932
  perceived_reputation =~
    X2.01                1.000                               0.834    0.943
    X2.02                1.062    0.039   27.491    0.000    0.886    0.917
    X2.03                1.087    0.033   33.378    0.000    0.907    0.966
    X2.04                0.618    0.055   11.173    0.000    0.516    0.595
  e_trust =~
    X3.01                1.000                               0.863    0.945
    X3.02                0.652    0.054   12.188    0.000    0.563    0.630
    X3.03                1.050    0.033   32.156    0.000    0.906    0.951
    X3.04                0.484    0.055    8.803    0.000    0.418    0.498

Regressions:
               Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  e_trust ~
    perceivd_rpttn  0.162    0.030    5.328    0.000    0.157    0.157
    quality_servic  0.865    0.036   24.229    0.000    0.875    0.875
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Fig. 4. The results of r programming using the lavaan library.

Fig. 4 describe the results depicted demonstrate that each variable possesses a corresponding p (>|z|) or p-value below 0.05. This finding implies that every specific latent variable holds substantial influence over the latent dependent variable. Notably, each independent latent variable presents a p-value below 0.05, indicating its significant impact on shaping the performance of e-trust [17]

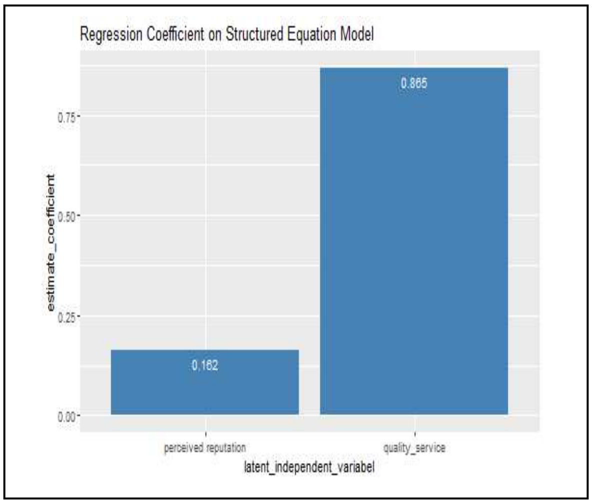

Fig. 5. The results regression coefficient on the structured equation model.

Fig. 5 describe reveals that service quality exerts the most significant influence, as evidenced by the estimated coefficient value of 0.865. Perceived reputation follows closely with a coefficient of 0.162. These results, obtained through the utilization of r programming, provide further confirmation of the substantial impact that service quality and perceived reputation have on the model.

B. Method k-nearest neighbors, multinomial naive bayes, stochastic gradient descent, and decision tree

Sentiment analysis involves discerning whether a given text conveys a positive or negative sentiment [10]. This research endeavors to develop a sentiment analysis methodology capable of predicting the sentiment expressed in comments on popular e-commerce platforms like bukalapak, tokopedia, shopee, and lazada [11]

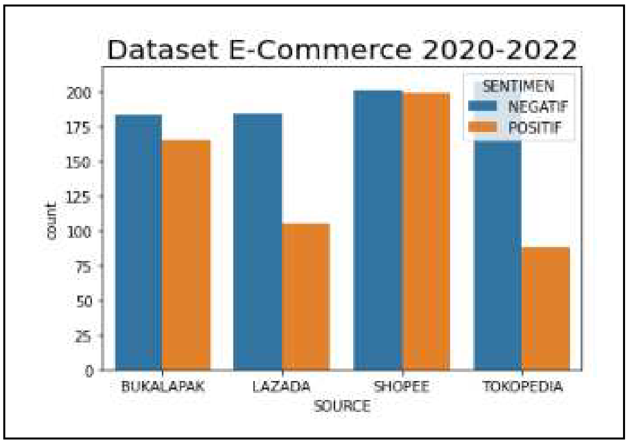

Fig. 6. Data visualization dataset e-commerce 2020-2022.

Based on the findings presented in Fig. 6, the trend graph reveals a notable upward trend in both positive and negative product review comments. This trend can be directly attributed to the influence of e-service quality and perceived reputation, which had a significant impact on e-trust levels concerning e-commerce seller accounts from 2020 to 2022. The prediction process utilizes various algorithms, including k-nearest neighbors, multinomial naive bayes, stochastic gradient descent, and decision tree. These algorithms are employed to forecast the outcomes and make predictions based on the available data.

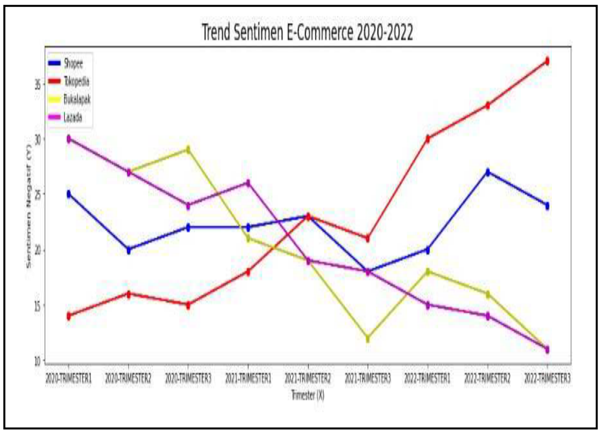

Fig. 7. Trend sentiment e-commerce 2020-2022.

Fig. 7 this finding is a dashboard report that shows a graph of the sentiment analysis trend. It shows increased negative comments regarding seller products related to the tokopedia company.

TABLE IV.
ACCURACY KNN, MNB, GRADIENT DESCENT AND DT

	K-nearest neighbor	**Multi nominal naïve bayes**	**Sgradient descent**	**Decision tree**
Accuracy	0.850	0.886	0.863	0.749
Precision	0.782	0.926	0.857	0.705
Recall	0.887	0.789	0.807	0.686
f1_Score	0.831	0.523	0.831	0.695

From Table IV, exhibits a classification report, providing a detailed comparison of the implemented algorithms. The accuracy values obtained for k-nearest neighbors, multinomial naive bayes, stochastic gradient descent, and decision tree are 0.849, 0.855, 0.863, and 0.748, respectively. From these results, it can be inferred that the multinomial naive bayes algorithm attained the highest accuracy among the tested algorithms. This comprehensive evaluation enables a thorough comparison of the outcomes, enhancing the overall analysis process.

VI. CONCLUSION

In conclusion, this research focused on conducting sentiment analysis of e-commerce sellers utilizing the algorithm model comparison learning algorithm. The findings revealed that the multinomial naive bayes model exhibited the highest accuracy of 0.886, followed by stochastic gradient descent with 0.863, k-nearest neighbors with 0.850, and decision tree with 0.749. The results obtained from the structured equation model highlight the significant impact of service quality (0.865) on perceived reputation (0.162). The regression coefficients provide valuable insights into the magnitude and direction of the relationships between these variables, highlighting the significant impact of service quality on shaping the perceived reputation. For future research, it is suggested to delve deeper and create a comprehensive model that assesses the extent of social media's influence on product brands within the e-commerce context. Such a model could shed light on how customer sentiment expressed on social media platforms impacts brand image and consumer decision-making in the digital marketplace.

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