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Measuring Credibility Level of E-commerce Sellers with Structural Equation Modeling and Naive Bayes on Tweets of Service Quality

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Abstract — **In digital development 4.0, store brands are very important. The problem in this research is the lack of consumer trust to buy quality goods in e-commerce store accounts so that it affects consumer satisfaction. This study aims to address this question feedback from the problems of the customer, then on the other hand a questionnaire with the PLS-SEM (Partial Least Squares Structural Equation Modeling) model to determine the dimensions of the variables selected according to customer experience. To achieve this aim, both negative and positive customer comments were compiled to assess customer satisfaction, employing a comparative analysis method through Naive Bayes algorithm. The overarching goal was to achieve optimal results and extract valuable insights regarding the determinants that influenced customer satisfaction within the domain of online transactions. This research also has an impact on buyers so they can have an understanding of the factors that support trust in customer satisfaction, so that individuals do not hesitate in making purchasing decisions to shop online.The results showed that the algorithm initially recorded a modest accuracy score of 0.37. Meanwhile, after implementing hyperparameter tuning, the accuracy increased significantly to 0.62. In the aspect of Smart PLS questionnaire analysis, a standardized Normed Fit Index (NFI) of 0.707 was recorded, which was slightly below the established threshold of 0.90. The standardized root mean square residual (SRMR) was measured at 0.071, falling below the specified value of 0.08, indicating a commendable model fit. However, the RMS theta value at 0.240 exceeded the threshold of 0.102.**

Keywords — E-Commerce, PLS-SEM, Seller Crebidility, Sentiment Analysis

I. Introduction

The COVID-19 pandemic from year 2019 to 2021 has significantly influenced shopping behavior, shifting from traditional market purchases to online shopping through e-commerce applications [1]. The inherent virtual nature of e-commerce is adding an extra layer of convenience to online purchases, catering to the preferences of consumers. However, these platforms are not devoid of challenges, as they often deal with issues such as disparities between product descriptions and actual merchandise, subpar product quality, and post-sales malfunctioning of products [2]. A pivotal facet underpinning successful online trading is the establishment of trust. Based on the indispensability of trust in this context, considerable research has been dedicated to dissecting trust factors and comprehending their profound influence on e-commerce platforms [3]. This research addresses a gap in previous studies, focusing on the prevalent issue of consumer complaints in online shopping. The existence of numerous fake accounts that provide misleading product recommendations has resulted in customers receiving goods that do not meet their expectations, either due to poor product quality or inaccurate descriptions. To address this, the research utilizes direct observation methods, interviews, and questionnaires with customers, along with the collection of positive and negative comments from (Company Jingdong) JD.ID seller accounts on the platform Twitter. Leveraging sentiment analysis (SA) serves as a potent tool to facilitate a deeper comprehension of user behaviors, perspectives, and responses. This analytical method stands poised to be integrated into a recommendation system (RS), thereby amplifying the precision of product recommendations [2] Sentiment analysis has become essential for e-commerce giants to capture user sentiment toward their products and leverage the research to entice users to purchase products [4]. In earlier research, a system collected tweets and used Support Vector Machine (SVM) to analyze sentiment, achieving an 86% accuracy in classifying tweets as positive or negative [7]. Previous research used qualitative data collected on open questions and data mining techniques to analyze vader sentiment analysis [21].

The previous research conducted public sentiment analysis on Twitter, focusing on the Shopee marketplace. Using the SVM algorithm with optimized hyperparameters through polynomial kernel tuning produced an impressive accuracy of 93.20% [8]. Additionally, this research explores the use of various naïve bayes algorithms, including multinomial naïve bayes, complementary naïve bayes, and bernoulli naïve bayes, to enhance the sentiment analysis process, because using hyperparameter tuning can improve accuracy for the better. Prior studies have formulated a model employing Multinomial Naive Bayes and LSTM techniques to predict pertinent and impactful emoji within tweets [20]. Based on previous research, the novelty of this research was found by observing problems with customers in PLS-SEM analysis, and then choosing variables based on customer experience to do a comparison of algorithms with algorithms, Gausian Naïve Bayes, Multinominal Naïve Bayes, Complement Naïve Bayes, Bernoulli Naïve Bayes and selecting the optimal parameters requires careful tuning, which can be a time-consuming process. Previous studies have collected customer feedback from websites and used the naive bayes and logistic tegression methods for sentiment analysis.[8]. Disadvantages of using the logistic regression method lacks the flexibility to assume certain functional forms and may not capture more complex patterns or interactions between variables [9]. The advantage of using the interpretability logistic regression method is to provide coefficient estimates that can be easily reported, allowing the researcher to understand the path of each predictor variable to the sentiment outcome. The principal contribution of this research is twofold, which includes the creation of PLS-SEM model from direct customer observations and a comparative assessment of the accuracy of Gaussian, Naive Bayes, multinomial Naive Bayes, complement Naive Bayes, and Bernoulli Naive Bayes algorithms. Subsequently, hyperparameter tuning is employed to achieve optimal accuracy.

II. LITERATURE REVIEW

Earlier research employed the Smart PLS tool for testing the model context through Partial Least Squares Structural Equation Modeling (PLS-SEM). The factors influencing e-commerce trust encompass information quality, inter-user quality, perceived privacy, perceived quality risk, and e-commerce awareness. These elements impact customer satisfaction, although they do not involve analytical engines [5]. In previous studies, the things that influence e-trust that impact e-satisfaction are service characteristics, basic services, personalized services, and social attributes [10]. In previous studies that affect customer satisfaction, trust impacts customers visiting, purchasing products again, and providing recommendations to friends [4]. While several service quality factors influence e-satisfaction,namely assurance, empathy, tangible, responsive, and reliability [5]. To ensure the utmost accuracy in sentiment categorization, a decision-making method has been devised for product recommendations [6]. Earlier research endeavors aimed at categorizing content into positive, negative, and neutral classes have commonly relied on review scores. These studies have strived to attain superior accuracy through the utilization of the LR + RF + SVM algorithm along with the TF-IDF feature (uni-gram + bi-gram + tri-gram). This approach has outshone alternative models, showcasing an achievement of the highest accuracy at 82% [7].

As opposed to an investigation that primarily focused on sentiment analysis of tweets using SVM, the current one presents novelty through a direct observation method. This method involves soliciting feedback and suggestions from consumers based on their real shopping experiences, thereby adding a unique vantage point to sentiment analysis in the realm of e-commerce. Earlier investigations have explored various E-Cyber threat intelligence indicators, including variables such as perceived privacy, perceived security risk, and customer awareness. The purpose was to unravel their influence on customer trust within e-commerce domain [5]. The current research strives to identify pivotal factors shaping customer trust in online transactions using PLS-SEM. Another research employed a structural model using the Analysis of Moment Structures (AMOS) to interlink indicators of electronic customer experiences with variables such as service features, basic service, and social attributes that impact customer trust [10]. This investigation probes into the interrelations between these factors, shedding light on the determinants of consumer trust in e-commerce. Similarly, some research applied a conceptual model to analyze PLS-SEM method. This model incorporates E-Customer quality indicators and considers variables such as assurance, tangibles, and responsiveness to ensure customer trust [11].

A contextual model has been employed to scrutinize the effects of user interface quality and information quality variables on electronic customer satisfaction. This analysis was conducted using PLS-SEM alongside E-trust quality indicators [5]. To assess satisfaction with anticipated purchases, indicators of electronic customer satisfaction has been incorporated, amalgamating variables, such as repeat visits and recommendations [10]. The innovative thrust of this exploration lies in the comprehensive amalgamation of diverse factors from prior research. This includes E-Cyber threat intelligence, E-Customer experience, E-Customer quality, E-Trust, and E-Customer satisfaction indicators. Collectively, these factors contribute to an extensive evaluation of the model through PLS-SEM, hence, augmenting the depth and scope of the analysis.

III. METHODOLOGY

The initial stage of this research encompassed the identification of customer concerns. This was achieved by randomly distributing questionnaires to 200 respondents who held consumer accounts on JD.ID (Jingdong Company). Based on this process, direct observations were performed through interviews and the administration of questionnaires to elicit responses and comments from the participants.

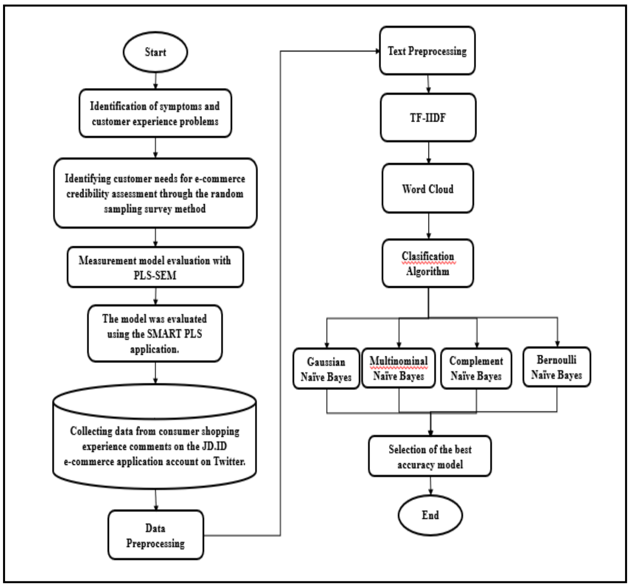

Fig 1. Flowchart methodology

An overview of the process, from inception to conclusion, was shown in Figure 1. Commencing with direct observations, questionnaires were distributed to gather responses and comments from the participants. Subsequently, several indicators from prior research were incorporated, including E-Cyber threat intelligence, E-Customer experience, E-Customer quality, E-Trust, and E-Customer satisfaction. The questions used in the direct observations could be seen in Table 1.

TABEL I QUESTION FOR RESPONDENTS

E-Cyber threat intelligence	**E-Customer Experience**	**E-Service Quality**	**E-Customer Trust**	**E-Customer Satisfaction**
(E-CT.01) perceived privacy Does the consumer have security knowledge about the release of personal data?	**(E-CX.01) service characteristic** Do the service and social attributes of e-commerce transactions affect customer trust?	**(E-SQ.01) assurance** Exists insurance coverage exist in the event that the items do not arrive or arrive damaged or not at all?	**(E-CT.01) user interface quality** Can both excellent and negative customer review input lead to e-commerce account system enhancements?	**(E-S.01) visit again** Does information security awareness, customer experience, service quality, customer trust affect customer satisfaction to buy goods again?
(E-CT.02) perceived security risk Are you aware of the risk of cybercrime in online buying and selling transactions on e-commerce accounts?	**(E-CX.02) basic service** Is there a basic service for returning goods if the receipt of a product purchase is not as expected purchased customer?	**(E-SQ.02) responsive** Is there a call center if there is one that is useful for solving customer problems?	**(E-CT.02) information quality** Is there product information that matches the quality of the product being sold?	**(E-S.01) recommend** Do factors such as information security awareness, customer experience, service quality, and customer trust have an impact on customer satisfaction and their likelihood to recommend the same seller account to their friends?
(E-CT.03, E-commerce awarness Is there customer awareness based on customer personal information in conducting data transactions?	**(E-CX.03) social attributes** Do social media comments affect product image on customer trust?	**(E-SQ.02) tangible** Are the delivered products of the quality according to the expectations of the customer's order?		

The third phase included evaluation of the model accomplished through bootstrapping, after the analysis of questionnaire results using the Smart PLS application. This assessment scrutinized the significance of path analysis estimates and process coefficients. Furthermore, to validate the alignment between customer inputs and comments within the application, data from Twitter discussions related to JD.ID buying and selling accounts were collated. The data preprocessing phase in sentiment analysis comprised several steps. In the first step, raw data was sourced from diverse outlets, such as social media platforms or customer reviews. Furthermore, data cleansing ensued, entailing the removal of redundant punctuation marks, special characters, and numerical data. After this refinement, the data went through tokenization, encompassing the segmentation of text into individual words or tokens. After tokenization, the tokens were subjected to normalization, which entailed converting the result to lowercase and eliminating stop words – commonly occurring words with limited semantic value, such as "the" or "and". Stemming or lemmatization was also applied to streamline words to their root form. Finally, the preprocessed data was primed for sentiment analysis. In this scenario, it was classified into distinct sentiment categories – positive, negative, or neutral – using a range of machine learning or natural language processing techniques. Based on this scenario, the text preprocessing stage was executed.

Text data was gathered from diverse social media platforms and customer reviews. The collected text went through cleaning, which entailed removing foreign elements such as special characters, punctuation marks, and numbers, thereby producing refined text data. The text was broken down into individual words or tokens through a process known as Tokenization, enabling more granular analysis at the word level. Subsequently, stop-word removal was employed to eliminate common and less significant words, such as "itu (it)," "dan (and)," or "adalah (is)," effectively reducing noise and enhancing analysis efficiency. To establish a uniform format across the text, normalization was employed to convert all words to lowercase and introduce diversity into the analysis. In the next step, stemming or lemmatization was conducted to reduce words to their base or root forms. Another aspect of focus was the cloud stage, which focused on calculating word frequencies in order to identify frequently occurring words and associated sentiment.

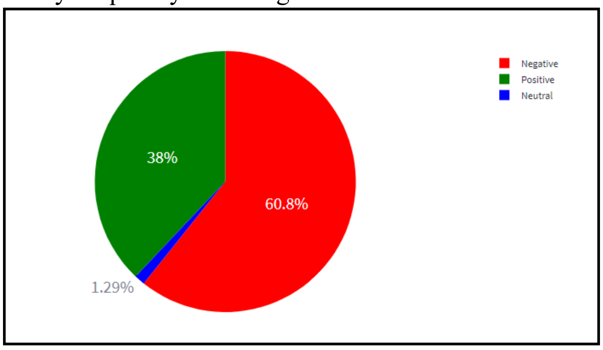

Fig 2. Customer comment data

This process facilitated word grouping based on similar meanings, effectively trimming data dimensions. For sentiment analysis, machine learning or natural language processing techniques were used to categorize processed text into sentiment categories namely positive, negative, or neutral. The final phase of the analysis assessed the accuracy of the best model. At this point, each data instance (text) received sentiment-based labeling. Positive labels indicated contentment, while negative labels denoted dissatisfaction.

This process was pivotal for training and evaluating machine learning models dedicated to sentiment analysis, using labeled data as a benchmark against the predictions of model. The Figure 2 above is a dataset of comments from customer buyers at JD.ID e-commerce. This dataset encompasses product reviews and comments submitted by Indonesian customers concerning JD.ID e-commerce accounts. The dataset comprises 60.8% negative comments gathered from 1178 respondents, 38% positive comments from 736 respondents, and 1.29% neutral comments collected from 25 respondents. This dataset is structured with six distinct columns: account, item, store name, account name, comments, and labels.

IV. Experimental Result

A, Evaluation of measurement model

Evaluation of the measurement model is pivotal in appraising the reliability and validity of the structural model. During that phase, the designated measurement model comes into play. In the initial step, model specification was executed to identify latent variables or constructs and to select suitable indicators for the research model. This entailed establishing connections and associations between the constructs and their corresponding indicators [11].

In the subsequent stage, methods for evaluating the measurement model focused on assessing the reliability and validity of both indicators and constructs. This encompassed scrutinizing factor loadings, composite reliability, convergent validity, and discriminant validity [11]. The factor loading was also assessed to measure the strength of relationships between the indicators and their corresponding constructs. Elevated loading factors indicated robust relationships between indicators and constructs [13]. Based on this outcome, the calculation of composite reliability gauged the internal consistency of indicators within each construct, with higher values signifying increased construct reliability. Convergent validity was then addressed to ensure strong interrelations among the indicators of constructs [13]. This was evaluated using the average variance extracted (AVE), assessing whether the value surpassed a predefined threshold. Subsequently, the focus turned to discriminant validity, aiming to ascertain the distinctness of indicators across different constructs. This evaluation encompassed a comparison between the square root of the Average Variance Extracted (AVE) value and the correlations among constructs. The anticipation was that the square root of AVE for each construct would exceed the correlations with other constructs [13].

A statistical metric within SmartPLS, used to evaluate the reliability and internal consistency of scales or questionnaires is Cronbach Alpha. This metric gauged the extent to which a set of items within a scale measured a common underlying construct [13]. An alternative to Cronbach Alpha was the reliability coefficient known as (Rho_A), which appraised the composite reliability of latent constructs within a SEM. This coefficient provided an estimation of the internal consistency of items affiliated with a specific construct [13]. The ensuing step entailed an examination of the outcomes derived from data processing in SmartPLS. The determination of the reliability of indicators hinged on achieving a minimum loading factor of 0.70. This threshold of 0.70 was rationalized by the requirement that latent variables ought to elucidate each indicator with no less than 50% of the reliability value (0.50). Indicators failing to meet this criterion were excluded from the measurement model [14]. Subsequently, the minimum recommended value of composite reliability, which was 0.70, was assessed. In exploratory research, it should be noted that Composite reliability values ranging from 0.60 to 0.70 might still warrant acceptance. An aggregate loadings value lower than 0.60 denoted inadequate dependency [15]. In line with the process, the assessment proceeded to validate the convergence by scrutinizing whether diverse indicators conceptually mirrored the same underlying concept, as unveiled through unidimensionality. The minimum acceptable value for AVE, a gauge of convergent validity, was set at 0.05 [13].
For the assessment of the explanatory power model, the R square evaluation employed values such as 0.75 (indicating strong), 0.50 (reflecting moderate), and 0.25 (signifying weak). Additionally, predictive relevance (Q2) employed the blindfold technique to gauge the cross-validated redundancy of each construct [16].

V. Evaluation Model

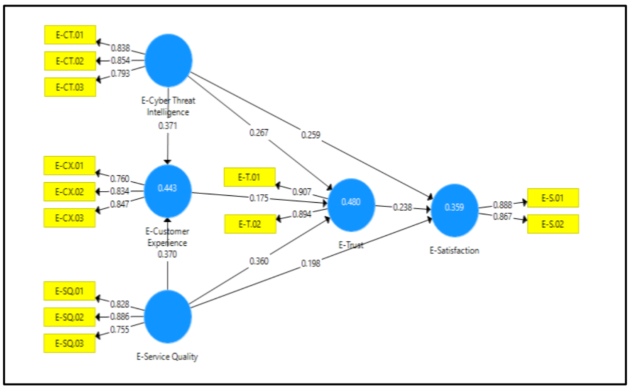

Fig.3 Loading factor on the final measurement model

Figure 3 represents the PLS-SEM model derived from amalgamating various factors established in prior studies. This integrated model underwent comprehensive analysis and evaluation, with a meticulous focus on achieving a significance level of Cronbach's alpha exceeding 0.07 [13]

TABLE III CROSS LOADING VALUE

Indicator	**Cronbach Alpha (>0.7)**	**rho_A (>0.7)**	**Composite Relibiality (>0.7)**	**Avarage Variance (>0.5)**
E-Customer Expericence	0,747	0,757	0,855	0,664
E-Cyber Threat Intelligence	0.772	0,777	0,868	0,687
E-Satisfaction	0,702	0,705	0,870	0,770
E-Service Quality	0,762	0,765	0,864	0,680
E-Trust	0,767	0,768	0,895	0,881

The outcomes of the aforementioned survey are presented in Table 3. Prior to undergoing evaluation, the measurement model had to go through a series of assessments, including convergent validity, model dependency, and discriminant validity [13].

B. Convergent Validity Analysis

In evaluating the measurement model, each indicator showed a loading factor surpassing 0.50. Moreover, The Composite reliability (CR) exceeded the 0.70 thresholds, and the AVE also surpassed 0.50, underscoring the presence of convergent validity [14].

C. Discriminant Validity

TABEL IV DICRIMINANT VALIDITY

	E-Customer Experience	E-Cyber Threat Intelligence	E-Satisfaction	E-Service Quality	E-Trust
E-CT.01	0.514	**0.838**	0.463	0.511	0.481
E-CT.02	0.497	**0.854**	0.460	0.536	0.540
E-CT.03	0.478	**0.793**	0.370	0.480	0.448
E-CX.01	**0.760**	0.465	0.331	0.405	0.370
E-CX.02	**0.834**	0.460	0.497	0.491	0.497
E-CX.03	**0.847**	0.536	0.410	0.553	0.467
E-S.01	0.421	0.481	**0.888**	0.491	0.442
E-S.02	0.477	0.434	**0.867**	0.396	0.466
E-SQ.01	0.490	0.585	0.380	**0.828**	0.542
E-SQ.02	0.551	0.520	0.439	**0.886**	0.493
E-T.01	0.509	0.579	0.451	0.599	**0.907**
E-T.02	0.480	0.486	0.479	0.531	**0.894**
E-T.03	0.434	0.413	0.434	0.755	**0.921**

Table 4 showed insight into Cross-loadings, which offered an alternate method to AVE for ascertaining the discriminant validity of reflective models.

D. Evaluation of model quality

It should be noted that the nature of PLS-SEM research was fundamentally exploratory. The research conceptually and practically bore a resemblance to multiple linear regression analysis, which endeavored to optimize the explained variance of the dependent variable. However, PLS-SEM extended this pursuit by encompassing evaluation of quality of the measurement model [18].

V. TABEL R-SQUARE

Matrix	**R Square**	**R Square Adjusted**
E- Customer Experience	0.443	0.438
E- Satisfaction	0.359	0.349
E- Trust	0.480	0.472

Table 5 showed the R-squared (R2) values, quantifying the extent to which one or more factors elucidated the variance of an exogenous variable. The R-squared criteria for significance were as follows, including above 0.75 (significant), between 0.50 and 0.75 (moderate), and below 0.25 (weak). PLS-SEM employed metrics to gauge model quality, specifically assessing its predictive capacity [13]. A pivotal metric utilized in this assessment was the standardized root mean square residual (SRMR), employed to evaluate the fit of the structural equation model (SEM). The SRMR quantified the discrepancy between the observed covariance matrix of the model and its implied counterpart.This evaluation averaged the standardized residuals, with lower values signifying a more favorable fit. Another metric, the Normed Fit Index (NFI), also played the role of quantifyinthe distinction between the observed and implied covariance matrices, thereby reflecting the data fit of the model [14].

TABEL VI THE MODEL FIT SUMMARY

	Saturated Model	**Estimated Model**
SRMR	0.071	0.074
NFI	0.707	0.703

Table 6 showed the results of the model fit testing, of which SRMR recorded a value of 0.071, below the threshold of 0.08, and NFI attained a value of 0.707, beneath the benchmark of 0.90. Consequently, both model fit assessments showed that the model did not meet the criteria for a satisfactory fit [13].

TABEL VII THE RESULT NAÏVE BAYES CLASSIFIER

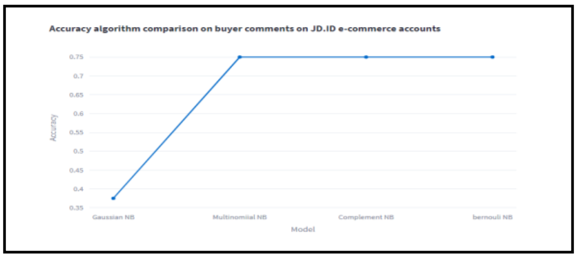

Fig.4 Word cloud Opion on commentar account e-commerce

Analyzing Figure 4, a comparative examination of the algorithms revealed a low accuracy reading for Gaussian Naive Bayes, at 0.37, necessitating improvement.

Fig.5 Word cloud Opion on commentar account e-commerce

According to Figure 5, JD.ID dataset showed the observations made regarding withdrawal comments, expressed in the Indonesian language. It should be noted that the terms such as "barang" (goods), "laptops," "penjualan bagus" (good sales), and "harga" (price) were recurrently employed by the public in tweets related to JD.ID, as seen in the accompanying word cloud.

TABEL VII QPRECISION,RECALL,F1-SCORE AND SUPPORT

	Precision	**Recall**	**F1-score**	**Support**
Positif	0.57	1.00	0.73	4
Negative	1.00	0.25	0.40	4
accuracy	0.625	0.625	0.625	8
Macro avg	0.79	0.62	0.56	8
Weight avg	0.79	0.62	0.56	8

Based on Table 7, after obtaining results from the Gaussian Naive Bayes algorithm, an accuracy score of 0.375 was attained. Consequently, a process of hyperparameter tuning was performed to enhance accuracy, culminating in a value of 0.625, which surpassed the previous value.

VI. CONCLUSION

In conclusion, the analysis of the questionnaire results employing Smart PLS yielded a NFI of 0.707, which fell below the 0.90 thresholds, and a SRMR of 0.071, below 0.08. Moreover, the Root Mean Square Theta (RMS Theta) was recorded at 0.240, failing to surpass 0.102. Based on these results, it could be inferred that the model was not congruent with the data. However, the research adhered to the requisite criteria for indicator variables, given that both Cronbach alpha and rho_A values exceeded 0.7, indicating robust reliability. A composite reliability value beyond 0.7 signified a robust internal consistency. An Average Difference value surpassing 0.5 also signified distinctions between constructs. In the aspect of sentiment analysis accuracy, the Gaussian Naive Bayes algorithm initially garnered a modest score of 0.37, then subsequent hyperparameter tuning bolstered its accuracy to 0.62. It should be noted that the accuracy of each kernel could be influenced by factors such as the employed dataset and selected parameter values. Future research needed to explore alternative sentiment analysis techniques to ascertain their potential in elevating the accuracy of algorithm classification. In the larger context, the results showed the necessity for refinement and further exploration, aimed at enhancing model fit and augmenting the accuracy of sentiment analysis algorithm.

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