ISSN: 2754-6683

Journal of Marketing & Supply Chain Management

Review Article

Open Access

Measuring Online Customer Satisfaction Based on Customer Reviews: Topic Modeling Method Using Latent Dirichlet Allocation (LDA) Algorithm

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ABSTRACT

Companies invest significant resources in retaining their customers. Nonetheless, organizations have witnessed customer attrition due to inadequate loyalty. This trend is particularly prevalent among online customer bases. The root cause of this issue lies in the absence of an effective tool for measuring online customer satisfaction that surpasses the capabilities of existing methods. To address this concern, a quantitative study explored the dimensions of online customer satisfaction measurement and established a model applicable across industries for gauging and predicting online customer satisfaction. This was accomplished by conducting an online survey via SurveyMonkey with 384 respondents, employing supervised and unsupervised machine learning techniques in conjunction with the topic modeling algorithm, Latent Dirichlet Allocation (LDA). The findings of this study revealed a significant relationship between predictor variables such as navigation, playfulness, information quality, trust, personalization, and responsiveness and the target variable, online customer satisfaction, employing multiple linear modeling (LSM). Furthermore, it was observed that this phenomenon transcends age groups, impacting both younger and older customers alike. However, it is essential to acknowledge certain limitations, including the risk of overfitting, challenges in establishing external validity, a narrow focus on the retail sector (B2C), and a restricted scope limited to the United States market.

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Received: December 26, 2023; **Accepted:** January 05, 2024; **Published:** January 09, 2024

Keywords: Online Customer Satisfaction, Online Reviews, Topic Modeling, Supervised and Unsupervised Learning.

Introduction

Satisfied customers are critical in fostering loyalty and driving long-term business profitability. This underscores the significance of customer satisfaction in ensuring sustainability [1]. O'Sullivan and McCallig established a robust correlation between customer satisfaction and marketing performance [2]. Some studies have also demonstrated customer retention mediates satisfaction and profits [3]. However, specific industries, such as FMCG and finance, encounter challenges related to increasing customer churn despite substantial investments in Customer Relationship Management (CRM) initiatives [4]. One major challenge organizations face is measuring online customer satisfaction and developing continuous marketing solutions [2]. Various models are employed for this purpose, including NCSI, SERVQUAL, MUSA, Probit/Logit, Important Performance Analysis, and Cluster Analysis. Nevertheless, these models have practical limitations, such as outdated customer sentiment measurement and industry-specific applicability [5- 7]. Recent extensive research on customer satisfaction has led to the development of constructs such as customer loyalty, retention, churn, performance-importance analysis, and customer consonance. Nevertheless, the current body of research has not yielded a versatile online customer satisfaction measurement model that can be applied universally across industries [1-2,8-11]. The present study aims to fill this void by introducing a model for assessing and predicting online buyer satisfaction, thus enabling more effective marketing decisions, enhanced customer retention, loyalty, and sustainable performance [10,12]. Li et al. emphasized the importance of online customer reviews to gauge satisfaction [13]. This study's significance lies in its capacity to offer insights that can enhance practices related to customer satisfaction measurement and potentially necessitate revisions to existing models within the current marketing landscape. As organizations increasingly emphasize customer orientation and relationship management, the findings from this study are poised to inform improved methodologies and marketing strategies, potentially leading to adjustments in marketing investments and the customization of offers to bolster long-term profitability [8,2].

Literature Review

Customer satisfaction measurement is crucial for organizations as it enables them to analyze the most exigent performance criteria and the organizational performance related to each criterion. The most widely used customer satisfaction measurement tools grounded in the literature appear ineffective in today's business context, especially given how customers share their sentiments with their friends and family network via social media [2]. This study seeks to model a customer satisfaction measurement model based on online reviews of customers interacting with organizations that conduct business by using online platforms.

• Customer Satisfaction

Satisfaction, primarily rooted in social psychology, has also found relevance in marketing but suffers from inconsistent definitions, leading to academic challenges in selection, operationalization, interpretation, and comparison of definitions [14,15]. The most grounded definition is an emotional or cognitive response focused on pre- and post-evaluation expectations and experiences. Critical attributes tied to this definition include response, focus, time, and evaluation [16]. Individuals assess their satisfaction across various experiences, like product purchases, friendships, service consumption, or test results [17]. Satisfaction evaluation typically encompasses overall satisfaction, addressing entire processes, and aspect satisfaction, which concentrates on specific service points within a process [18]. Organizations deem customer satisfaction vital for their survival. It correlates with customer retention, loyalty, and financial performance [19]. Customer satisfaction results from assessing the rewards and costs of purchase compared to expectations, acting as a bridge between expectations and perceived product performance [20-22]. Bhattacharya et al. identify two levels: micro (intrinsic) linked to individual perception and macro (extrinsic) compared with competitor offers [1]. Customer satisfaction is seen in post-purchase evaluations matching pre-purchase expectations, influenced by customer expectations and experiences [23,24]. However, Wang et al. argue that it is a socially constructed response to the customer-product-provider relationship, challenging existing definitions [9]. Factors like customer knowledge, equity, product performance, and discomfort moderate satisfaction [25]. Customer satisfaction results from disconfirming initial expectations [11]. It is rooted in anticipation and product delivery, leading to psychological discomfort when a product falls short of expectations [26]. An emotional response follows, gauging whether the product meets or disappoints [27]. This process defines customer satisfaction as the customer's psychological state evaluating if pre-purchase expectations match the product [10]. Lazaris et al. describe it as an impression forming after product or service use, shaped by the gap between expectations and post-consumption satisfaction [28]. It can also be seen as an individual's opinion, a reflective evaluation based on the overall experience involving the stages of need, evaluation, purchase, consumption, and post-consumption evaluation [29,30].

• Customer Online Reviews

Customer opinions on social media strongly impact consumer attitudes, engagement, and brand choices [31]. Electronic word-of-mouth (e-WOM) in virtual groups has become a powerful tool for shaping positive brand images [32]. Social interactions in e-WOM are driven by motives like social connections, economic incentives, altruism, and self-esteem [33]. Weblog users are seen as highly credible, especially in institutionally related domains [24]. Social media sites have gained preference over company and government websites [34], and the quality and quantity of consumer reviews significantly influence purchase intentions [35]. Customer reviews are pivotal for purchase decisions and loyalty, with virtual communities playing a crucial role driven by social identity, anticipated emotions, and desires [24,36]. The seller's response to online customer reviews is critical for communication managers [37]. Analyzing and monitoring online reviews is essential for managing consumer attitudes and opinions. Neglecting negative reviews can harm an organization and impact consumer buying behavior [39]. Opinion seekers are highly influenced by e-word of mouth, especially in adopting online opinions, driven by technological advancements like Web 2.0. Consumers actively participate in virtual communities, motivated to share reviews for explanation and critique [12,24,40]. The accuracy of evaluations depends on the volume of reviews, with more postings enhancing accuracy [41]. Accumulating reviews exponentially boosts a product's conversion rate, though users tend to focus on the first few reviews [42,43]. With technology and virtual communities, traditional word-of-mouth has evolved into e-word-of-mouth, enabling consumers to gather product information online before making purchase decisions [44].

• Network Theory

Online reviews are influenced by network theory, a concept embraced across various fields [45]. In a network, relationships are represented by nodes and arrows, with relationship strength dictating ideas and information spread [46]. Network theory explores how network structures impact individuals and groups, examining properties, relationship types, and central figures [47,48]. The power within a network is defined by the standards for coordinating social interactions, and being a network member invests in social relations for returns, known as social capital [49,50]. Key network concepts include centrality, cohesion, and structural equivalence and social networks play a pivotal role in information diffusion, shaping connections for initiating, relaying, and adopting innovation-related information through various forms like friendship, advice, communication, or social support [51-53].

• Text Mining

Text mining, also known as data mining or knowledge discovery from textual databases, extracts valuable patterns from unstructured text [54]. It is a part of Knowledge Discovery in Databases (KDD), which uncovers logical configurations in data [55]. Text mining involves four stages: information extraction, text data mining, database knowledge discovery, and information retrieval [17]. Information extraction gathers facts from text, while text data mining explores patterns using algorithms, machine learning, and statistics, often requiring preprocessing with natural language processing (NLP) [56]. The process culminates in knowledge discovery databases and answering specific questions. Text mining is a complex task due to the unstructured nature of text data and differs from data mining. Standard text mining methods include Latent Semantic Analysis (LSA), Probabilistic Latent Semantic Analysis (PLSA), and Latent Dirichlet Allocation (LDA) [57]. LSA reduces vector space via singular value decomposition, PLSA employs conditional probability theory, and LDA fits a topic model based on word frequency [58-60].

Methodology

This study sought to ground an online customer satisfaction measurement model based on customer reviews. In support of the above research objective, this study was nested on two critical learning approaches: unsupervised and supervised learning. The unsupervised learning encompassed text mining for topic modeling using the Latent Dirichlet Allocation (LDA) algorithm, while the supervised learning algorithm was used for linear modeling for predictions [57]. With the prior consent received from thirty (30) retail companies that conduct online businesses and use the customer reviews scraped from their websites, created the main word corpus for topic modeling using "topicmodels" package with "ggplot2" and "dplyr" in RStudio [58]. The word corpus created was subsequently used for tokenizing words and sentences, stopping- noise management on characters, and stemming-merging similar words [57]. The following equation was used for topic extraction.

$$P(Q|S) = \sum_{t \in T} P(Q|t, S) * P(t|S)$$

Where:
Q = Query
S = Satisfaction
t = Topic

Where P(Q|*t*, S) is the probability of generating query Q given topic t and satisfaction S. By assuming conditional independence between Q and S, P(Q|*t*, S) is simplified to P(Q|*t*). In the above process, every document created by web scraping is considered a mixture of topics, and every topic is a mixture of words [57]. A log ratio was used to distinguish between symmetrical topics. The word-topic probabilities were calculated based on yielded beta scores (β *word 1 + β * word 2 + β * word 3). Based on eigenvalues (see Table 1), greater than two were employed as a topic selection parameter to include in the final model.

Table 1: Eigenvalues

Predictor	Navigability	Playfulness	Info-Quality	Trust	Personalization	Responsiveness
Eigenvalue	2.004	2.002	2.026	2.132	2.154	2.009

Source: RStudio (Version 4.1.2)

The above calibration resulted in six (k = 6) topics influencing online customer satisfaction: navigability, playfulness, information quality, trust, personalization, and responsiveness.

- **Questions and Hypotheses**

This study aimed to design and ground a customer satisfaction measurement model that provides solutions to the limitations associated with the most used models in professional settings and academia. These limitations include the incapability to measure customer online customer satisfaction levels promptly and more relevant for organizations to make timely decisions, apprehend only customer past satisfaction experience, and the lack of predictive power associated with the models [5-7]. Based on the above phenomenon, the research addressed the following research questions

1. What relationship existed between the independent variables (navigation, playfulness, information quality, trust, personalization, and responsiveness) and the dependent variable (online customer satisfaction)?
2. Was there a difference between the younger and older online customers associated with overall customer satisfaction when interacting with online business transactions?
3. What was the degree of influence of the independent variables (navigation, playfulness, information quality, trust, personalization, and responsiveness) on the dependent variable (online customer satisfaction) when predicting customer satisfaction?

The following hypotheses were tested to ascertain the relationship between the independent and dependent variables, the degree of customer satisfaction, and the influence of independent variables on online customer satisfaction. $H_0$1. There is no relationship between all the independent variables and the dependent variable. H_a1. A significant relationship existed between at least one independent and dependent variable (Westlund et al., 2008). $H_0$2. The level of online customer satisfaction between the two age groups (young and old) was similar. H_a2. The level of online customer satisfaction between the two age groups (young and old) was different [6]. $H_0$3. No independent variable considered in this study significantly influences online customer satisfaction ($\beta_1+\beta_2+\beta_3+\beta_4+\beta_5+\beta_6=0$). H_a3. At least one independent variable in this study significantly influences online customer satisfaction [7].

- **Instrument**

An instrument was developed based on the six topics (features) modeled and related words (dimensions) captured from the LDA algorithm employed. A pilot study used a sample of thirty (n=30) retail customers via SurveyMonkey. A scale of 1-5 was used to measure all the dimensions [62]. Those who had at least three or more online transaction experience within the last two months at the point they took the survey was employed as a qualifying criterion to partake in the survey administered. A linear regression was employed to find the answer to research question one, a two-sample t-test was employed to answer question two, and a least squares method (LSM) was employed to answer question three during the pilot phase of the study. Internal reliability was established with a reliable alpha score (α = .8) [63-65]. As a result, all the constructs were retained for a full-scale study [66-67]. Internal validity was established with a reliable correlation coefficient score (r = .7). In contrast, construct validity was established with an adjusted R-squared score of .79. A full-scale study was administered using a sample of three hundred and eighty-four (n=384) [68].

Model Fitting and Prediction

The primary model entailed one target and six predictor variables. The target variable is the online customer satisfaction (Y). The model's intercept (β_0) measures the degree of variance of online customer satisfaction when all the predictor variables are zero. The predictor variables considered in the model include navigation (X_1), playfulness (X_2), information quality (X_3), trust (X_4), personalization (X_5), and responsiveness (X_6).

$\boldsymbol{Y}=\beta_0+\beta_1\ Nav+\beta_2\ \text{Play}+\beta_3\ \text{Info:Qual}+\beta_4\ \text{Trust}+\beta_5\ \text{Person}+\beta_6\ \text{Response}+\epsilon$.

Based on the above model, the coefficients (β) for all the predictor variables were obtained to measure online customer satisfaction.

Training and Testing

A 10-fold (k=10) cross-validation, a resampling technique, was used for model evaluation and to reduce the risk of overfitting. A tenfold was determined as a rule of thumb to avoid biases and variance [69]. The average Mean Squared Error (MSE) was estimated using the following MSE formula to evaluate the model's overall performance on the entire data set during cross-validation.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y_i})^2$$

Findings

- **Relationship**

Multiple linear regression examined the relationship between the predictor variables (navigation, playfulness, information quality, trust, personalization, and responsiveness) and the response variable (online customer satisfaction). There was a significant relationship between online customer satisfaction and navigability (a lower navigability score correlated with higher online customer satisfaction, β = -.101, *p* = .048) and playfulness (a lower playfulness score correlated with higher online customer satisfaction, β = -.140, *p* = .006) [70]. However, there was no evidence to suggest a correlation between online customer satisfaction and the rest of the predictor variables (information quality β = -.056, *p* = .278, trust β = -.029, *p* = .593, personalization β = -.022, *p* = .687, and responsiveness β = -.030, *p* = .552) due to higher *p*-values yielded than the .05 calibrated level. The R^2 was .034, which means 3% of the variance in online customer satisfaction can be explained by the model containing navigability and playfulness, $R(384) = .185$, $R^2 = .034$, $F(6, 377) = 2.228$, $p = .04$. Based on the above findings, the test was significant and rejected the first null hypothesis. The evidence suggested a significant relationship existed between at least one independent and dependent variable.

• Age Groups

Preliminary data screening showed that scores in both groups met the assumptions of equality of variance with Levene's test and were insignificant ($F = .159$, $p = .691$), indicating that the assumption of homogeneity of variance had been met. Despite a difference between the two age groups, there seemed to be an overlap between those that had to be explored in detail using t-statistics. Two population means were compared using the two-sample *t*-test to see if they were equal. In this study, the two groups considered for the *t*-test are the younger and the older generations based on the age parameters set for each group [71]. The two age groups did not differ significantly, t (382) = -1.613, p = .11, 95% CI [-.56, .06], d = -.17. The mean satisfaction for the young customer group (M = 2.78, SD = 1.45) was not significantly different from the older customers group (M = 3.04, SD = 1.46) with a negative Cohen's d effect size (d = -.17). Based on the above findings, the null hypothesis, the level of online customer satisfaction between the two age groups (young and old) was not different, was accepted.

• Influence

Per the model summary and the ANOVA outputs, the overall model predicted approximately 3% of the variance in online customer satisfaction, $R^2 = .034$, F (6,377) = 2.228, p = .040.

Based on the coefficients depicted in the coefficient table (see Table 2), there was a significant influence of navigability (a one-unit increase in navigability decreases online customer satisfaction by .101 units, β = -.101, *p* = .048) and playfulness (a one-unit increase in playfulness decreases online customer satisfaction by .140 units, β = -.140, *p* = .006) on online customer satisfaction when predicting [70]. Based on the above findings, navigability and playfulness significantly influence online customer satisfaction when predicting customer satisfaction and rejected the third null hypothesis. The evidence suggested that at least one independent variable in this study significantly influences online customer satisfaction.

Table 2: Coefficients

							95% CI		Collinearity Statistics	
Model		Unstandardized	Standard Error	Standardized	t	p	Lower	Upper	Tolerance	VIF
H_0	(Intercept)	2.951	0.074		39.855	< .001	2.805	3.096		
H_1	(Intercept)	5.147	0.699		7.368	< .001	3.773	6.520		
	Navigability	−0.020	0.010	−0.101	−1.982	0.048	−0.039	-1.534×10^{-4}	0.995	1.005
	Playfulness	−0.021	0.008	−0.140	−2.770	0.006	−0.036	−0.006	0.997	1.003
	Info_Quality	−0.011	0.010	−0.056	−1.087	0.278	−0.032	0.009	0.974	1.026
	Trust	−0.004	0.007	−0.029	−0.534	0.593	−0.017	0.010	0.883	1.133
	Personalization	−0.002	0.005	−0.022	−0.403	0.687	−0.012	0.008	0.866	1.154
	Responsiveness	−0.014	0.024	−0.030	−0.595	0.552	−0.062	0.033	0.991	1.009

Source: JASP (Version 0.16.4)

• Predicting Satisfaction

A systematic feature selection procedure was implemented to determine the optimal number of features to predict overall customer satisfaction. Consequently, based on the Akaike Information Criterion (AIC) assessment, which yielded a score of 1386.43, it was ascertained that all predictor variables remained indispensable for the precise prediction of overall customer satisfaction. A ten-fold (k = 10) cross-validation technique was executed following the selection process to derive an estimate for the Mean Squared Error (MSE). The resultant computed delta was within the range of 2.142187 to 2.138727. Subsequent to the above MSE estimation, online overall customer satisfaction was assessed by comparing actual satisfaction scores against the corresponding predicted scores (denoted as y and ŷ, respectively). The actual and predicted scores for overall customer satisfaction of the initial ten observations, i.e., the first ten customers, have been elucidated in Table 3 for reference.

Table 3: Satisfaction Prediction

Customer	1	2	3	4	5	6	7	8	9	10
Actual (1-5 scale)	4	3	5	3	2	4	2	2	1	3
Predicted (1-5 scale)	2.9	3.0	3.0	3.0	2.9	2.9	3.2	2.9	2.9	3.2

Source: RStudio (Version 4.1.2)

As discerned from the tabular data in Table 3, a notable observation emerged, indicating that the first, third, and sixth customers were not anticipated to exhibit satisfaction according to the employed set of predictors, considering their quantity and inherent characteristics. Conversely, it is noteworthy that all other customers listed in the table are projected to manifest a state of satisfaction based on the predictive modeling outcomes.

Discussion

Online customer satisfaction, crucial for businesses, stems from interactions with their online presence. With the internet's growing role in shopping and communication, it has become a pivotal metric [72-76]. Feedback surveys, online reviews, social media monitoring, and website analytics offer insights into website quality, purchase ease, and customer service responsiveness. Enhancing website functionality, providing courteous service, offering personalized recommendations, and responding effectively to feedback can boost satisfaction [14]. Prioritizing online customer satisfaction can enhance reputation, foster loyalty, and drive sales. Online customer satisfaction, vital for businesses, has surged due to increased internet use. Metrics like surveys, reviews, social media monitoring, and analytics gauge it by assessing website quality, purchase ease, and customer service [14,15]. Enhancing website functionality, offering personalized recommendations, and responding promptly and courteously can bolster satisfaction and enhance reputation, loyalty, and sales. Organizations must gauge customer satisfaction across all channels to connect with customer attitudes and behavior [77]. Key indicators include purchasing behavior, customer growth, and financial performance [78]. This holds for both online and in-person interactions. Surprisingly, online customer satisfaction surveys are often neglected [79-82]. Online measurement should align with the digital e-commerce strategy, focusing on criteria like navigability, playfulness, information quality, trust, personalization, responsiveness, and overall satisfaction [83-85].

Different customer segments have distinct online transaction behaviors. The study found that contrary to expectations, playfulness and navigability equally influenced the satisfaction of both younger and older generations; however, increasing the complexity of these factors negatively affected overall satisfaction. This aligns with prior research, highlighting customer frustration with complexities in playfulness and navigability. Companies should prioritize simplicity in web design, process, and engagement to enhance online strategy [74,86-87]. Notably, this phenomenon is unique to this study. Efficient website navigation is essential for a positive user experience [88]. To achieve this, websites should feature clear and consistent navigation menus on every page. Using descriptive labels for menu items helps users understand their purpose, reducing confusion. Logical content organization and grouping related information simplify information retrieval. Visual aids like dropdown menus and breadcrumbs enhance user orientation [89]. User testing and feedback collection identify areas for improvement. By considering these factors, organizations can enhance website navigability and provide a better online buying experience.

Playfulness enhances online engagement and creates memorable website experiences [90]. Using vibrant colors consistent with the brand adds a playful touch. Micro-interactions, like bouncing buttons or loading animations, inject dynamism [91-92]. Playful language, such as puns and jokes, reflects a friendly brand personality. Playful illustrations break up text and simplify complex ideas. Interactive elements like quizzes educate and engage customers, but it is vital to balance playfulness with functionality [74]. Information quality is crucial for a positive user experience and trust-building [93]. It hinges on accuracy, relevance, clarity, authority, and timeliness. Accuracy ensures credibility, relevance aligns with purpose, clarity promotes understanding, and timeliness keeps content current and relevant. Trust is paramount for website success, influencing visitor attraction, retention, conversions, and goal achievement [79-81]. Trust hinges on credibility, user experience, conversion, reputation, and search engine ranking. Credibility fosters trust by establishing reputation and confidence. Positive user experiences promote interaction and desired actions. Trust aids conversions by addressing visitor concerns. It builds a positive reputation, driving brand loyalty and advocacy. Search engines reward trust with higher rankings, increasing visibility and traffic.

Personalization tailors a website to individual user needs and has several key benefits [74,86-87]. It enhances user experiences by offering relevant content and features, boosting engagement and loyalty. Personalization increases conversions through tailored recommendations and calls to action. It provides a competitive edge by creating a distinct and memorable user experience. Data-driven insights from personalization inform improvements in design, content, and functionality. This enhances user service and business outcomes. Moreover, personalization fosters loyalty by meeting user needs, promoting retention, and advocacy. Responsiveness, the ability to adapt to various devices, is vital for websites for multiple reasons [83-85]. It enhances user experience across devices, boosting engagement and loyalty. A responsive site reaches a broader audience, improving traffic and brand visibility. Search engines favor responsive sites, leading to higher rankings and visibility. Additionally, it is cost-effective, saving resources on development and maintenance. Responsive websites remain future-proof, adapting to new devices for long-term relevance and effectiveness. This study highlights the significance of playfulness and navigability in influencing overall online customer satisfaction. Increased playfulness and navigability were observed to hurt customer satisfaction when interacting with commercial organizations. However, information quality, personalization, and responsiveness showed no significant influence. While this study emphasizes the role of playfulness and navigability in customer satisfaction, it does not encompass all factors affecting it. Interestingly, online customers expressed satisfaction with transactions as long as website playfulness and navigability remained uncomplicated [88,91-92].

Limitations

As with any other study, this study also has a few limitations. Firstly, the predictor variables explained that the overall satisfaction (response) variance was only 3%, leaving 97% unexplained by the fitted model. Additionally, the Adjusted R-squared estimate suggested weaker parsimony of the fitted model. Based on the above premise, the fitted linear regression model was an overfitting model, a key limitation of this study [94]. Secondly, a cross-sectional design was employed for this study. A longitudinal study yields more reliable results than a cross-sectional study, particularly when measuring customer satisfaction. Thirdly, this study is narrow-focused by only considering the retail sector (B2C) and being limited to the United States market. Considering the above limitations underscored, it is recommended that any potential research in the same direction carefully consider them to increase the study's validity [95-97].

Conclusion

The investment made by companies in retaining customers has been substantial; however, the challenge of customer attrition persists, especially in the realm of online customer bases. The absence of a robust tool to effectively measure online customer satisfaction has been identified as a key contributor to this issue. To tackle this concern, a comprehensive quantitative study was conducted. This study delved into the dimensions of online customer satisfaction, culminating in a versatile model applicable across industries for evaluating and predicting online customer satisfaction. The results unveiled a substantial correlation between key predictor variables-navigation, playfulness, information quality, trust, personalization, and responsiveness-and the pivotal variable of online customer satisfaction. Notably, this influence was observed across different age groups, impacting younger and older customers.

Conflict of Interest Statement

The author has no conflicts of interest to declare. Author seen and agreed with the contents of the manuscript and there is no financial interest to report. I certify that the submission is original work and is not under review at any other publication.

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