Self-service business intelligence and customer satisfaction: The moderating effects of independent non-technical users

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Abstract

Purpose: Purpose: The study examines how self-service business intelligence affects customer satisfaction in terms of system quality, user training effectiveness, data accessibility, and the moderating effect of non-technical user. It aims to clarify the relationships between these variables and how they affect the experiences of customers in businesses that use self-service business intelligence tools in technology-based small businesses in Lagos State Nigeria.

Design/methodology/approach: The study adopts quantitative research design using survey method, The sample size of 250 was established with the Research Advisor Table, with a confidence level of 95% and a margin of error of 5%. To mitigate the problem of non-response, suitable actions were implemented, resulting in the incorporation of an extra 75 respondents, constituting 30% of the initial sample. The modification yielded a final sample size of 325 from various industries including retail, finance, manufacturing and healthcare. A structured and validated closed-ended questionnaire was used for data collection. A total of 300 copies of the questionnaire were filled and returned for analysis, with a response rate of 92.0%. Relationships between constructs, the moderating effect of non-technical user independence and customer satisfaction were investigated using regression analysis.

Findings: Findings show that customer satisfaction is greatly impacted by self-service business intelligence (system quality, user training effectiveness, and data accessibility) of technology-based small firms in Lagos State Nigeria. The inverse relationship between the moderating role of non-technical user independence shows that a greater degree of independence combined with less support may result in mistakes that reduce customer satisfaction.

Limitations and Research Implications: Future research should adopt constructs that were not used in this study.

Practical implications: The study's practical application indicates that in order to assist non-technical end users in handling data responsibly, organisations should invest in robust self-service business intelligence systems, extensive training programs, and easy access to data in addition to support mechanisms.

Originality/value: The study sheds light on the intricacy of self-service business intelligence and customer satisfaction with a focus on independent non-technical user. It provides practitioners and scholars looking to maximise the usage of self-service business intelligence with enlightening inputs.

Keywords: Business intelligence, Business performance, Customer-Centric strategies, Customer insights, Data Visualization, Self-service Analytics, Nigeria

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Introduction

Self-service business intelligence, which enables non-technical users to independently understand data and develop insights without the assistance of IT departments, has revolutionised the way businesses use data. Consumer satisfaction is complicatedly impacted by the process of making data more standardised or accessible, even though it provides greater flexibility and cost savings (Izzuddin & Abidin, 2025; Naidu et al., 2025). The effectiveness with which teams convert data into customer-focused decisions is unbalanced, as evidenced by studies showing that user-associated issues, such as inconsistent skill levels and irregular tool use, frequently hinder the adoption of self-service business intelligence (Bakır & Sak, 2025; Lennerholt et al., 2021). This poses important questions: *does business intelligence affect customer satisfaction and does the moderating role of non-technical user influence self-service business intelligence attributes and customer satisfaction in technology-driven small firms?* Although self-service drivers, such as economy, convenience, and system dependability, are identified in the literature as sources of consumer value, the important role that user independence plays in mitigating these effects is not taken into account (Dang & Nguyen, 2023; Su, 2021; Wang, 2024).

Organisations have uneven user adoption and misinterpretation of information that might unintentionally degrade service quality, even while self-service business intelligence may enable faster customer response (Su, 2021). According to Borodako et al. (2023) and Ibrahim et al. (2025), technological functionality alone is insufficient to produce desired customer results, and system design components like response time and aesthetics are crucial for maintaining user attention (Ellitan et al., 2022; Wang, 2024). These discrepancies highlight a fundamental disconnect: businesses invest in self-service business intelligence infrastructure, but they lack the frameworks necessary to combine the desire for customer satisfaction with the analytical liberty of non-technical users (Andrade & Tumelero, 2022; Soeharso, 2024).

The purpose of this study is to close this gap by examining the effect of self-service business intelligence and customer satisfaction the moderating role of non-technical users in technology firms small businesses in Lagos State Nigeria. In order to maximise customer experiences and employee empowerment, this study examined how the independence of non-technical users interacts with self-service business intelligence systems. A noticeable gap in scholarly discourse that mostly looks at self-service business intelligence's operational advantages rather than its interactions with customers is filled by this dual focus (Izzuddin & Abidin, 2025; Lennerholt et al., 2021). The results of this study could inform future implementation strategies by ensuring that improved customer satisfaction, rather than a disjointed or misdirected analytics endeavour, is a reflection of a more standardized, accessible data with greater flexibility and cost savings.

Literature Review

Self-Service Business Intelligence

Self-Service Business Intelligence (SSBI) has evolved as a game-changing approach to business analytics, redefining how organisations perceive, access, and exploit data. Compared to traditional BI, where analytics and reporting tend to be centralised in IT departments, SSBI offers easy-to-use, low- or no-code solutions that democratise analytical capabilities across business users, irrespective of technical affinity (Lennerholt et al., 2021; Maghsoudi & Nezafati, 2023). This democratisation of information is commended for pushing decision-making more rapidly and nimbly, thereby removing age-long barriers related to IT resource dependence (Ramasamy et al., 2024). However, although promising more user empowerment and responsiveness, the research warns against the obstacles that follow broad adoption, particularly in terms of system quality, user capacity, and organisational performance (Andrade & Tumelero, 2022; Brunner et al., 2025).

System Quality

There exists a considerable body of work that conforms to the assumption that system quality is crucial to both adoption and effective utilisation of SSBI by non-technical users (Ellitan et al., 2022; Izzuddin & Abidin, 2025). Superior SSBI settings characterised by strength of infrastructure, usability, reliability, and velocity are more properly accepted and exploited, resulting in increased decision-making and, ultimately, higher customer satisfaction. In contrast, design difficulties, delayed processing, or lack of easy-to-use interfaces have been proven to undermine trust in data outputs, thus undermining the predicted benefits of SSBI (Soeharso, 2024; Ellitan et al., 2022). It alludes to a major paradox: while SSBI attempts to simplify analytics, failed implementation might compound user irritation, resulting in decreased utilisation and a terrible customer experience. The SSBI shift places a priority on user training, not only to familiarise users with technology but to promote data literacy and critical thinking (Amiruddin et al., 2024; Wang, 2024).

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User Training

Training is yet another essential element, having self-service business intelligence tools. Effective training helps users to engage with dashboards, interpret findings, and retrieve actionable insights for customer-facing activities. But the literature is rich with evidence that inadequate or occasional training delivers unequal adoption rates and mixed effectiveness among teams (Izzuddin & Abidin, 2025), requiring ongoing upskilling accompanied by technology adoption. Another companion and occasionally controversial issue is the degree of autonomy offered to non-technical users. Autonomy can increase innovation and speed by minimising IT dependence for analytics. However, experts indicate that over-self-governance without oversight can result in misinterpretation of data, poor decision-making, and undesired repercussions on customers' results (Kumah et al., 2025; Shojaei & Burgess, 2022; Naidu et al., 2025). The developing understanding is that the best configuration is to be balanced: users need freedom to obtain data but need to have access to validation processes and help to assure analytical quality (Amiruddin et al., 2024; Lennerholt et al., 2021).

Data Accessibility

Data accessibility refers to how easily users may access and utilise the information they require within the self-service business intelligence system. For SSBI to attain its full potential, unrestricted data accessibility is crucial. Open, integrated access to real-time and relevant information enables employees to respond rapidly and properly to consumer demand (Ramasamy et al., 2024). Still, issues such as system fragmentation, access restriction policies, or data silos remain a fact on the ground (Maghsoudi & Nezafati, 2023), with tendencies to yield decisions falling short of customers' expectations, thereby undermining the strategic objectives of SSBI adoption (Zungu et al., 2025). This conflict between technological competence and operational expertise emphasises the issue of transforming analytical infrastructure into consumer value.

Non-Technical User Independence

Non-technical user independence in self-service business intelligence (SSBI) is the level to which people without formal data or IT experience may independently access, evaluate, and acquire insights from data without continual IT intervention (Kumah et al., 2025; Shojaei & Burgess, 2022). Scholarly work indicates that where non-technical consumers operate with insufficient training or in the absence of adequate supervision, the autonomy to interpret information independently may lead to misinterpretation or omission of crucial specifics (Maghsoudi & Nezafati, 2023; Naidu et al., 2025). These inaccuracies damage accuracy and dependability of insights, which, when they reach customers, may further aggravate a reduction in quality and conversely affect satisfaction results.

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Besides, in line with the Technology Acceptance Model's ideas, user autonomy implies not only perceived usability but also necessary support systems to enable appropriate interpretation of results (Amiruddin et al., 2024; Lennerholt et al., 2021). Research also confirms independence and support balance via which users are enabled to investigate and make use of SSBI instruments but within the scope of verification and assistance offered by IT governance and organisational regulations (Borodako et al., 2023; Amiruddin et al., 2024). The balance promotes innovation and responsiveness with a negligible risk of data misappropriation that undoes customer satisfaction. However, non-technical user independence has a complex, moderating influence on the relationship between SSBI characteristics and customer satisfaction.

Customer Satisfaction

Customer satisfaction, which is often measured in terms of repeat purchase intent and service quality ratings, is typically considered the cornerstone of business success. When consumers' requirements are consistently met, whether through prompt or personalised service, they are more likely to remain loyal and come back (Wang, 2024). Aguiar-Costa et al. (2022) and Brunner et al. (2025) indicated that satisfaction is not just a result but also a continuous process that fosters trust and encourages recurrent engagement. This connection gets stronger in self-service business intelligence (Su, 2021). Organisations must make sure the insights produced by SSBI technologies closely match the needs and values of their customers because decisions are data-driven rather than human-to-human. Even the best data analytics can fail to influence positive customer experiences in the absence of such alignment (Zungu et al., 2025).

Theoretical Review

Two foundation theories inform the analysis of Self-Service Business Intelligence (SSBI) dynamics and customer satisfaction: the Expectancy-Disconfirmation Theory (EDT) and the Technology Acceptance Model (TAM). Rather than using each theory alone as a separate lens, this study blends them to reflect both the user adoption process and consequent customer satisfaction outcomes, allowing for a full picture of SSBI effectiveness.

Expectancy-Disconfirmation Theory

Expectancy-Disconfirmation Theory (EDT) depicts customer satisfaction as a cognitive process of evaluation in which consumers establish expectations before they experience a product or service and then evaluate actual performance results with their expectations (Kumah et al., 2025). Satisfaction happens when performance equals or surpasses expectations, and the effect is good behavioural intentions such as recurrent purchases (Ramasamy et al., 2024). In the SSBI context, EDT reveals how usability and quality of business intelligence outputs; insights, reports, and dashboards directly influence a customer's value perception and satisfaction. EDT, nevertheless, focuses mostly on post-use evaluation and does not explain how consumers originally engage with and accept technology that delivers these outputs. So, whereas EDT grounds customer satisfaction knowledge in result alignment terms, it requires a parallel model to explain antecedent user behaviour.

Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) addresses this criterion by focusing on technology use and adoption factors, particularly for non-technical users (Borodako et al., 2023; Izzuddin & Abidin, 2025). TAM says that perceived usefulness and ease of use influence people's attitudes and inclinations to adopt technology. In SSBI systems, these perceptions affect whether users believe they can and desire to use analytics tools independently for decision-making. When users regard SSBI tools as accessible and valuable, independent and frequent utilisation ensues, which is needed for producing the level of insight stated in EDT. Thus, TAM illustrates the behavioural underpinnings necessary for the realisation of technology-enabled performance that impacts customer satisfaction (Brunner et al., 2025).

Integrating EDT and TAM

The integration of EDT and TAM provides a theoretical foundation that is sequential and interactive. TAM highlights the methods by which non-technical users embrace and use SSBI systems effectively, highlighting the effects of system quality, user training, and data availability on perceived utility and ease of use. It is this acceptance and capabilities of the user that regulate the development of accurate, timely, and relevant insights (Izzuddin & Abidin, 2025; Kumah et al., 2025; Lennerholt et al., 2021; Shojaei & Burgess, 2022). Thus, combining TAM and EDT allows this study to capture both the antecedents of technology use and the downstream evaluation of technological outcomes, offering a comprehensive framework for studying SSBI's impact on customer satisfaction in technology-based small firm.

Theoretical Framework

In order to explain how self-service business intelligence affects customer satisfaction the moderating role of independent non-technology user, this study's theoretical model posits SSBI system quality, user training, and data availability as crucial antecedent variables to influence non-technical users' ease of use and utility perceptions in line with TAM. This model emphasises that facilitating SSBI adoption by non-technical end-users (abetted by technology quality and training) is both necessary and not sufficient on its own; user autonomy must be balanced with adequate support to ensure insights consistently meet or exceed customer expectations effectively (Andrade & Tumelero, 2022; Lennerholt et al., 2021). Briefly, the model captures a dynamic relationship: TAM discusses the conditions under which SSBI tools are embraced and, in reality, employed by non-technical workers, enabling service performance; EDT shows how such performance promotes customer pleasure through expectation matching. This integrated perspective increases the knowledge of how SSBI, as tempered by user autonomy, influences customer satisfaction in shifting business situations ((Amiruddin et al., 2024; Izzuddin & Abidin, 2025).

Empirical Review

Amiruddin et al. (2024) examined how organisational environment and non-technical elements affect the quality of systems, information, and services, as well as how user satisfaction is affected in petrochemical manufacturing companies. Questionnaires were used to gather quantitative data from ERP users at five different managerial levels, ranging from general managers to supervisors. The study, which used Structural Equation Modelling Partial Least Squares (SEM-PLS) analysis, found that organisational climate influences the important success criteria for ERP adoption. User happiness was found to be directly impacted by system and information quality, demonstrating the value of a supportive organisational context in guaranteeing ERP implementation success. According to Buhasho et al. (2021) for most firms, business intelligence remains a priority, and significant investment is being attracted to this field. Nevertheless, current research provides fragmented and ambiguous insights into the extent to which this technology is efficiently translated into useful business learning. The study examined the relationship between business intelligence capability and firm performance and how organisational capabilities affect it. Supported by theories of organisational learning and information systems capability, the study employed a mixed-methods approach, using thematic analysis for qualitative data and structural equation modelling (SEM-PLS) for quantitative data. Organisational competence positively supports this link, according to the results, providing managers, policymakers, and researchers in the field with new information.

Borodako et al. (2023) examines the relationship between innovation orientation (IO), which is comprised of six dimensions market, organisational culture, technology, human resources, and structural process and organisational performance (OP). Knowledge management (KM)

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serves as a mediator and technological readiness (TR) as a moderator. The model was validated by experimenting with data from business service firms using route analysis and multiple regression. The findings supported six out of eight hypotheses, demonstrating that KM is positively impacted by strategy, technology, organisational culture, and market factors, which partially mitigate their impact on performance. Additionally, TR makes the connection between knowledge management (KM) and company performance easier to understand, emphasising the need for effective KM and better results.

According to Izzuddin and Abidin (2025) Customers can independently purchase services using self-service technology (SST) via equipment such as automated stations, kiosks, and self-checkout devices. Businesses employ SST to boost competitive advantage, productivity, and service quality. However, it's important to comprehend how customers view the quality of SST services and how that affects loyalty. Izzuddin and Abidin (2025) used a quantitative methodology based on the SSTQUAL model and cognition-affective-behavior theory. Via online surveys, 285 McDonald's SST users between the ages of 18 and 55 were polled. Functionality, enjoyment, assurance, design, and convenience are the five aspects that makeup SST service quality, according to the report. Good customer satisfaction increases customer loyalty.

Wang, (2024) examined how consumer satisfaction in the post-COVID-19 economy is affected by digitalisation in global business. The SERVQUAL model of service quality was used in the research to operationalise satisfaction using a mixed quantitative approach that included surveys and trials. Digital improvements increased data security, order processing speed, packing, product range, alerts, and reliability, according to 3,796 customer reviews in four AliExpress stores. When chatbots were introduced, customer satisfaction dropped because they provided less individualised care and empathy. The study advances our knowledge that not all forms of digitalisation are equally popular with consumers, highlighting the significance of gauging satisfaction before fully implementing new digital solutions for global trade.

According to Su, (2021), a lot of research has been done on service quality, particularly since self-services have changed how consumers interact with businesses to get positive outcomes including ease, security, and positive behaviour. Su, (2021) examines the driving forces behind consumers' intentions to use self-service, with a particular emphasis on the role that customer value plays as a mediator. 35 Taiwanese self-service consumers' data were analysed using structural equation modelling. The results show that consumer value is greatly impacted, albeit to differing degrees, by convenience, cost savings, security, and ease of use. It was also shown that the relationship between these and behavioural intentions was mediated by customer value. These findings imply that self-service should be a priority for Taiwan's service industry in order to encourage repeat business and consumer loyalty.

Synthesising Theoretical Perspectives

Theory underpinning SSBI research is most likely to be derived from Expectancy-Disconfirmation Theory (EDT) and the Technology Acceptance Model (TAM). EDT operationalises customer satisfaction as a function of alignment (or misalignment) of anticipated and actual service results; in SSBI, this means that technology-based performance must be at or above customers' expectations in a bid to establish loyalty and trust (Kumah et al., 2025; Ramasamy et al., 2024). TAM responds to the adoption dynamics, presuming that perceived ease of use and usefulness are the prime drivers of user adoption of new technology, increasingly applicable in the context of willingness on the part of non-technical users to operate SSBI tools autonomously (Borodako et al., 2023; Izzuddin & Abidin, 2025).

Research Gaps and the Current Study

Despite an increasing stream of studies investigating the technical and operational benefits of SSBI, much remains unknown, including most significantly how the non-technical user independence forms the link between SSBI adoption and customer happiness in technology-driven small firms. Past studies have primarily accounted for technical or manpower factors with little understanding of the interactions of such factors in real life to produce meaningful customer impacts, especially in developing economies such as those found in Lagos State, Nigeria, with their unique structural and market complexities. This research solves these gaps by presenting non-technical user independence as a fundamental moderating variable and customer happiness explicitly as the main outcome variable.

Hypotheses Development

Based on the pooled literature, the following hypotheses are spelt out completely for empirical testing: *H_{01}: There is no significant positive relationship between self-service business intelligence; system quality, user training adequacy, and data accessibility and customer satisfaction in technology-driven small firms. H_{02}: non-technical users do not significantly moderate self-service business intelligence; system quality, training adequacy, and data accessibility to customer satisfaction in technology-driven small firms.*

This alternative hypothesis is based on the reviewed literature that both highlights the promise and risk of SSBI adoption. While the evidence does verify beneficial effects with appropriate conditions (system quality, user training adequacy, and data accessibility and customer satisfaction), the continued variability of organisational contexts and user capacities needs exact empirical assessment. This comprehensive literature review anchors the study in established theory, interweaves empirical paradoxes and trends, and positions the current study as an obligatory contribution to the knowledge base of how SSBI, enabled through non-technical user agency, influences customer satisfaction in technology-enabled small firms.

Methodology

The study adopts a quantitative survey research design and rely on the prior study methodology of Adeyemi, and Olubiyi (2024); Adeyemi, and Olubiyi (2023). The quantitative design is useful since it provides systematic measurement and statistical testing of relationships hypothesised in the study's objectives and hypotheses. Surveys enable the collection of standardised data from varied businesses, and in doing so, generalizable information regarding trends and relationships among variables. The target population were technology-driven small firms in Lagos State such as retail, finance, manufacturing, and health. Lagos State is an appropriate place due to the fact that it is Nigeria's hub of economic operations and a top location for the absorption of new technology.

Stratified random sampling technique was employed to assure representative coverage by industry sector and enhance the precision and generalizability of results. The strata were selected by industry classification (finance, healthcare, manufacturing, retail), suggesting diverse operating settings that can influence SSBI uptake and customer satisfaction dynamics. Within industry strata, firms were randomly selected to participate and offered proportional coverage based on available demographic data for the industry. The initial sample size was determined via Cochran's formula and Research Advisor Table, targeting a 95% degree of confidence and 5% margin of error with 250 respondents. In order to account for probable non-response bias and boost statistical power, an additional 30% oversampling was undertaken, bringing the sample up to 325 individuals. The final sample includes the four industry stratum selected respondents, proportionally assigned to reflect their proportion in the population of technology-based small firms in Lagos State.

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Data were obtained using a validated self-completion questionnaire with closed-ended items scored on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree) as depicted in Appendix 1. The survey questionnaire was created from established scales based on prior research, tailored for the SSBI and customer satisfaction scenario of small firms. The survey questionnaire was pilot-tested with a pilot sample to establish clarity, construct validity, and internal consistency, where Cronbach's alpha coefficients were above 0.70 for all the scales. Data collection was handled by the lead researcher and trained research assistants who gave the surveys in person to ensure high rates of response and to resolve participant queries.

Descriptive statistics were then produced to summarise respondent demographic information and provide a description of the shape of data distribution. Inferential statistics, like multiple regression and moderation analysis, were performed to evaluate hypothesised correlations between SSBI components, non-technical user autonomy, and customer satisfaction. All analyses were performed using the Statistical Package for the Social Sciences (SPSS) version 26.

Ethical criteria were adhered to throughout every stage of study. Participants were informed of the study aim, assured of confidentiality and anonymity of responses, and granted voluntary informed consent before participation. Data were securely stored in encrypted modes known only to research members, in conformity with data protection guidelines.

Results and Discussion

Result and data analysis

From the 325 copies of the questionnaire distributed by the researcher and trained research assistants, a total of 300 copies of the questionnaire were filled and returned for analysis representing a response rate of ninety-two percent (92%) from technology based small businesses in Lagos State Nigeria. Response rate is the percentage of people who responded and administered copies of the questionnaire in the survey The rest were either unreturned or had missing responses, however, the total number of questionnaires received was sufficient to represent the population, and they were analyzed. The detail of the responses is shown in Table 1.

Table 1

Response Rate

	Frequency	Percentage %
Completed usable copies of the questionnaire	300	92.0
Unreturned/Incomplete copies of the questionnaire	25	8.0
Total received	325	100.0

Source: Researchers' computation

Demographic Data Interpretation

The demographic information gives an in-depth understanding of the research participants, capturing their varied experiences and backgrounds in relation to self-service IT products in technology-based small businesses in Lagos State Nigeria (see Table 2). The distribution across industries is balanced, with participants selected from manufacturing, healthcare, retail, finance, and other areas, guaranteeing that the results reflect a diverse organisational environment. Operations specialists, marketing managers, data analysts, and customer service agents were among the many employment types that would provide a thorough grasp of how various activities interact with self-service business intelligence technologies.

Table 2
Demographic Information of Respondents

Variables	Categories	Frequency	Percent
Age	18-25	33	11.0
	26-35	124	41.3
	36-45	90	30.0
	46-55	53	17.7
	Total	**300**	**100.0**
Gender	Male	153	51.0
	Female	147	49.0
	Total	**300**	**100.0**
Educational Qualification	Secondary	15	5.0
	Bachelor's Degree	57	19.0
	Master's Degree	160	53.3
	Others	68	22.7
	Total	**300**	**100.0**
Job Role	Data Analyst	124	41.3
	Marketing Manager	90	30.0
	Operation Specialist	53	17.7
	Customer Support	33	11.0
	Total	**300**	**100.0**
Experience with SSBI Tools	Less than 6 months	52	17.3
	6-12 months	117	39.0
	1-3 years	93	31.0
	Over 3 years	38	12.7
	Total	**300**	**100.0**
Industry	Retail	71	23.7
	Finance	118	39.3
	Manufacturing	56	18.7
	Healthcare	24	8.0
	Others	31	10.3
	Total	**300**	**100.0**

Source: Research Field Survey

Table 2 shows the demographic information of the sample for the self-service business intelligence use study is broad and evenly distributed, with the majority of participants falling into the 26–35 age range (41.3%) and the 36–45 age range (30%), which represents a young to mid-career workforce. With men making up 51% and women 49%, the gender distribution is almost equal, guaranteeing that the results are inclusive of all genders. Nearly one-fifth of the respondents had a bachelor's degree, and more than half (53.3%) have a master's degree, indicating a highly competent sample that will be able to use SSBI tools efficiently. As would be expected of regular users of SSBI systems, data analysts make up the largest category for job functions (41.3%), followed by marketing managers (30%). Experience with the SSBI tool varies; 39 percent of respondents have used it for 6–12 months, while 43.7% have used it for more than a year. This suggests that there is a mix of novice and seasoned users. Retail (23.7%) and finance (39.3%) are the two industries with the greatest industry participation; both sectors are known for using a lot of data, but manufacturing, healthcare, and other sectors also contribute insightful viewpoints.
Table 3 shows the results of the regression analysis indicate that there is a substantial correlation between customer satisfaction and the predictor variables of self-service business intelligence: system quality, data accessibility, non-technical user independence, and user training adequacy. The model's correlation coefficient (R) value of 0.966 indicates that these variables and the outcome variable have a strong relationship. More significantly, the model's total impact of the predictors accounts for roughly 93.4% of the variation in customer satisfaction, as indicated by the R Square value of 0.934. Taking into account the number of predictors and sample size, the model's strength and generalisability are further supported by

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its modified R Square of 0.933. Furthermore, the model's predictions are accurate and reliable, as evidenced by the comparatively low estimated standard error of 0.281.

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Table 3

Regression Analysis

Model	R	R Square	Adjusted R Square	Std. Error Estimate
1	0.966[a]	0.934	0.933	0.28130

a. Predictors: (Constant), Non-Technical User Independence, Data Accessibility, System Quality, and User Training Adequacy

Source: Researcher's Field Survey

Table 4 shows the regression analysis's ANOVA that the model is a very significant predictor of customer satisfaction. The overall impact of the predictors non-technical user independence, data accessibility, system quality, and user training adequacy on customer satisfaction is statistically significant, according to the F-value of 1042.739 and the associated p-value of.000. This indicates that there is very no probability that these outcomes could have happened by accident, proving that the model accurately explains the shift in consumer satisfaction. The regression sum of squares' high value (330.053) in relation to the residual (23.344) further supports the idea that the predictors are mostly responsible for the outcome's variability.

Table 4

Regression showing the significance of each predictor to Customer Satisfaction

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	330.053	4	82.513	1042.739	0.000[b]
	Residual	23.344	295	0.079		
	Total	353.397	299			

b. Customer Satisfaction

Source: Researcher's Field Survey

Table 5 regression coefficients show how significantly each predictor contributes to customer satisfaction on its own. A standardised coefficient (Beta) of 0.198 indicates a substantial and positive relationship between system quality and customer satisfaction, suggesting that improvements in are linked to higher levels of customer satisfaction. The highest positive effect is produced by user training adequacy, which has a beta of 0.777, indicating that successful training programs significantly increase user empowerment and satisfaction. The significance of having simple access to pertinent data is demonstrated by the positive relationship between data accessibility and customer satisfaction (Beta = 0.627). Unexpectedly, the moderating role of non-technical user independence exhibits a substantial negative correlation (Beta = -0.612), indicating that, in this situation, higher degrees of user independence are linked to worse customer satisfaction. This would imply that greater independence will result in incorrect interpretation and abuse of knowledge with detrimental effects if neither proper assistance nor direction is provided. In the self-service business intelligence environment, all the predictors have substantial roles in forecasting customer satisfaction, as evidenced by the fact that they are all $p < 0.001$.

Table 5
Contribution of each predictor to Customer Satisfaction

Model		Unstandardized Coefficient		Standardized Coefficient	T	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.277	0.016		140.180	0.00
	System Quality	0.216	0.035	0.198	6.188	0.00
	User Training Adequacy	0.845	0.044	0.777	19.359	0.00
	Data Accessibility	0.681	00.028	0.627	24.208	0.00
	Non-Technical User Independence	-0.666	0.054	-0.612	-12.250	0.00

Source: Researcher's Field Survey

Discussion of Results

This study examined the effect of self-service business intelligence and customer satisfaction the moderating role of non-technical users in technology-based small firms. Consistent with existing literature, the results show that SSBI system quality, user training, and data accessibility have positive significant correlations with customer satisfaction (Su, 2021; Izzuddin & Abidin, 2025; Amiruddin et al., 2024; Lennerholt et al., 2021). Intriguingly, high-quality SSBI system fosters user confidence, enabling employees to generate insights that are consistently accurate and timely in fulfilling customer needs. Meanwhile, effective training provides users, especially those without extensive technical backgrounds, with the necessary skills to utilise these systems in the best possible manner.

Furthermore, access to relevant and integrated data enhances the capacity to make valid, customer-centric decisions. These findings validate the recognition that successful SSBI deployment is not just a function of technology itself but also organisational processes and people skills. The findings also validate key assumptions of the Technology Acceptance Model (TAM), which argues that perceived quality and ease of use of technology are strong predictors of technology adoption and usage, having an indirect influence on customer satisfaction. The findings are also in line with the Expectancy-Disconfirmation Theory (EDT) in demonstrating that when employees are supported with contextual guidance and productivity tools, they are more likely to meet or exceed customer expectations through timely and accurate service delivery. However, the study found an unexpected and intriguing trend regarding non-technical user autonomy as a moderating factor.

Contrary to many existing studies claiming that greater user autonomy enhances technology adoption and organisational outcomes (Shojaei & Burgess, 2022; Borodako et al., 2023; Kumah et al., 2025), also, this result showed a negative moderating effect of non-technical users on the relationship between SSBI characteristics and customer satisfaction. While empowering non-technical users tends to accelerate decision-making and drive innovation, excessive freedom, if not paired with sufficient training, can lead to data misinterpretation and flawed decision-making that eventually takes away from customer experiences. This means that unchecked autonomy can inadvertently reduce SSBI value, reflecting the risks of uncontrolled user freedom in data-driven environments. This paradoxical result emphasises the complexity of SSBI settings and chimes with cautions in the literature concerning the risks of unfettered autonomy (Borodako et al., 2023). These findings help to underline the need for a balance between empowerment and control: users must have enough freedom to explore data, but within frameworks that provide verification, monitoring, and ongoing guidance to prevent errors that could subtract from customer satisfaction.

From a practical perspective, the evidence suggests that technology-based small firms, particularly in emerging nations such as Nigeria, complement investments in SSBI infrastructure with comprehensive training programs, continuous user support, and

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articulated governance policies aimed at maintaining data integrity. This balanced approach aligns with the two-level governance framework proposed by Andrade and Tumelero (2022) and Brunner et al. (2025), where IT departments retain control while granting users carefully managed autonomy so that insights remain reliable and customer outcomes are optimised.

Theoretically, the study contributes to literature by extending TAM and EDT models by incorporating non-technical user autonomy as a crucial moderating variable. The study highlights that technology acceptance and use and the resulting customer satisfaction are influenced not only by system characteristics but also by quintessentially human and organisational variables mediating technology impact. Hence, the evidence substantively rejects the alternative hypotheses, confirming that SSBI attributes significantly influence customer satisfaction and that non-technical user autonomy plays a complex moderating role.

Implications of the Study

These results have substantial implications for the organisations implementing self-service business intelligence. Researchers stress that, while important, investing in top-notch technology and thorough training alone is insufficient. Organisations must also continue to supervise and support non-technical users in order to help them use data ethically. In the absence of this equilibrium, greater independence may unintentionally lower consumer satisfaction. Consequently, companies ought to endeavour to establish a setting in which users feel both empowered and encouraged to utilise self-service business intelligence products.

Contribution to Knowledge

This study contributes to the body of literature by shedding light on self-service business intelligence and customer satisfaction, the moderating role of non-technical users in technology-based small businesses in Lagos State, Nigeria. The study examined the intricate relationship between the moderating effect of non-technical user independence in the self-service business intelligence settings and customer satisfaction, which has been underappreciated. It adds to the current knowledge of how human factors and technology work together to affect customer satisfaction, providing a deeper comprehension of the adoption and usage of self-service business intelligence systems.

Conclusion

This study examines effect of self-service business intelligence and customer satisfaction the moderating role of non-technical users in technology-based small businesses in Lagos State Nigeria. It emphasises that the main factors influencing customer satisfaction in businesses are the quality of self-service business intelligence systems, efficient user training, and information accessibility. These elements enable users to make wiser choices that enhance client experiences. Additionally, according to the study, giving non-technical users too much independence without adequate assistance lowers customer satisfaction, maybe as a result of miscommunications or information abuse. This emphasises how crucial it is for businesses to strike a delicate balance between promoting user independence and offering sufficient direction. In the end, human factors- which allow users to utilise data responsibly are more important for effective self-service business intelligence adoption than technological ones. Businesses can increase their chances of gaining a competitive edge and satisfying customers by serving both.

According to the conclusions of the study, managers in technology-enabled small firms need to pay top importance to the creation of self-service business intelligence (SSBI) systems in order to enhance customer satisfaction. In particular, Managers need to invest in obtaining or constructing SSBI tools that are responsive, user-friendly, and dependable so that employees can create accurate and timely insights. Apart from basic technical skills, managers should create and implement periodic training programs that strengthen the employees' data literacy and analytical ability. Facilitating manipulation by non-technical users to speed up decision-making, managers need well-established guidelines, supporting infrastructures, and verification procedures built to counter dangers of misinterpreting data and bad decision-making consequences.

The conclusions also contain crucial implications for policy-makers at organisational and government levels who have a role to play in developing effective digital transformation ecosystems. Policymakers would encourage the creation and deployment of standardised SSBI implementation guidelines that balance user autonomy with good data governance and quality assurance. While this research contributes to SSBI and customer satisfaction in technology-based small firms' knowledge, future research might examine in which cultural settings and industry sectors the interplay between SSBI, user independence, and customer happiness differs, to establish contextual moderators.

Despite the satisfactory results in relation to the hypothesis, the research acknowledged several limitations and also experienced significant limitations, some of these are considered to be useful precursors for future study. Primarily, the data was gathered from a limited sample within the technology-based small business sector. The focus of the study on only technology-based small firms in Nigeria, restricts the applicability of its results. The findings and implications of this article are specific to Nigeria and focused mostly on small business sector, which might restrict the generalizability of the results. Although limited, the findings of the current study should inspire scholars to do more comprehensive research on self-service business intelligence and customer behaviour. The paper's cross-sectional design limits the author's ability to assert causation.

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Appendix 1

Questionnaire

System Quality

1. Our SSBI tool interface is easy to use
2. Insights generated by the system are always accurate
3. The speed of query processing is satisfactory
4. The dashboards and reports are visually appealing
5. Technical issues or system downtime are not often

User Training Adequacy

1. Training prepares you to analyze data independently
2. Training material is important to your everyday work
3. I often need extra help following training
4. I apply what I learned from SSBI training in real work scenarios
5. Updates or advanced training are conducted very often

Data Accessibility

1. I simply reach out to cross-departmental data
2. Limitations of data often slow me up when it comes to decision-making
3. I measure the clarity of the data governance policies.
4. Data that I see when using SSBI tools are up-to-date
5. Data available to you to use in analyzing customer-related data is comprehensive.

Non-Technical User Autonomy

1. I confidently generate insights without using IT
2. I often validate results with others?
3. I am independent when it comes to customizing SSBI dashboards

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4. I often ask for new analysis or reports on initiative
5. I feel empowered to make decisions from data analysis

Customer Satisfaction

1. I would always suggest these services to a friend or a colleague?
2. Customers often repeat business following the use of insights from our SSBI tools
3. SSBI-driven decisions impacts service quality.
4. SSBI tools help make customer experiences more personalized
5. I feel satisfied with the promptness with which customer problems are resolved using SSBI insights?

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