



## Gaining customer insights in big data for SMEs market segmentation decisions in emerging markets

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**Abstract.** Small and medium enterprises around the world, and especially in emerging markets, face challenges when it comes to market segmentation. They have limited knowledge of the importance of big data customer insights for making concrete market segmentation decisions. The purpose of this study was to assess gaining customer insights in big data for market segmentation decisions of SMEs in emerging markets. The results of the study indicated that customer behaviour analysis strongly affects market segmentation decisions of among small and medium scale enterprises. A beta-value of 0.344 was shown to indicate that a unit change in customer behaviour analysis will lead to a unit change in market segmentation decisions among small and medium scale enterprises with the t-statistics of 4.608 and p-value of 0.001. It was specified that customer preference analysis strongly affected market segmentation decisions of among small and medium scale enterprises. The results showed that the beta-value was 0.379, indicating that a unit change in customer preference analysis will lead to a unit change in market segmentation decisions of among small and medium scale enterprises with the t-statistics of 6.654 and p-value of 0.001. It was revealed that customer feedback analysis strongly affected market segmentation decisions of among small and medium scale enterprises, the results showed that the beta-value was 0.215 also indicated that a unit change in customer feedback analysis will lead to a unit change in market segmentation decisions of among small and medium scale enterprises with the t-statistics of 3.155 and p-value of 0.002. It was concluded that gaining customer insight in big data was essential for small and medium enterprises in emerging economy to make effective market segmentation decisions

**Keywords:** complex data; customer behaviour analysis; customer feedback analysis; customer perspective; customer preference analysis

### Introduction

Market segmentation is important as it helps companies to allocate resources better, improve customer engagement, and thereby increase overall profitability. However, T. Tavor *et al.* (2023) criticised market

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segmentation for being dated, when it relied on generalised or partitioned models, since they do not cater to the needs of different customer groups in an age that was rapidly changing and filling up with competition. Treating customers as a single group generally results in very wide markets that overlook crucial intelligence on consumers, which, in turn, backfired on marketing strategies, which then do not turn up high profits. This problem was aggravated for SMEs (Small and Medium Enterprise), in the case of emerging markets as they have low amounts of data and cannot pull together sophisticated analytical tools.

When compared on a global scale, especially against emerging markets, SMEs were certainly up against a challenge while trying to divide their market during their segmentation process. Limited resources force them to cut back on their expenditures for market research tools, which results in relying on instincts or incomplete data. On top of that, S. Oduro (2020) posited that SMEs, especially in African and Asian countries, have low exposure to the digital world and unsteady market conditions, which rendered the basic segmentation methods useless. The researcher stated that this mismatch between the tools that SMEs have access to and it immensely caters to a place, where improvement was needed. Unlike other studies that focused primarily on customer demographics, this research emphasised behavioural and preference data to provide more actionable insights.

There were efforts at the global level to improve market segmentation for SMEs, including digital transformation and capacity building in data analytics. Various programmes by governments and international organisations aim at increasing access to big data technologies and market intelligence tools for SMEs. Moreover, Z. Samira *et al.* (2024) agreed that larger corporations and tech firms have started offering scalable solutions that allowed SMEs to perform more granular segmentation using customer insights from digital channels. However, these efforts often remained fragmented and failed to reach the most resource-constrained SMEs, limiting their overall effectiveness.

These programmes have had a sporadic impact on SMEs. Whereas the digital transformation programmes have given some the capacity to enhance their market segmentation using better data capture and analytics, many still fall into bad or wrong segmentation decisions due to inconsistency or inaccuracies due to the absence of a coordinated strategy for customer insight. All this exacerbates the limited application of data-driven approaches, given that consumer behaviour in diverse markets – whether they were rural or underserved – was generally not well comprehended. According to O. Abdul-Azeez *et al.* (2024), SMEs mostly failed to optimise market opportunities. With big data promising many changes in almost every other operational aspect, the research gap on how SMEs in emerging markets can take full advantage of customer insights towards effective market segmentation still remains significant. Most

literature involved large enterprises with abundant resources, hence leaving SMEs underrepresented, especially those in resource-constrained settings. Moreover, O. Abdul-Azeez *et al.* (2024) noted about the specific scenarios of SMEs in emerging markets; this may include infrastructure limitations and differences in consumer behaviour across regions. It was important to point out these gaps to create solutions that can be scaled up and implemented for practicality by SMEs. This research will seek to propose a new framework that will integrate customer behaviour analysis, customer preference analysis, and customer feedback analysis into market segmentation decisions for SMEs in emerging markets. Emphasising these three core areas, the study will provide a comprehensive perspective on how SMEs might make use of big data in refining segmentation strategies.

By using customer insights with big data, SMEs will significantly enhance their market segmentation decisions. Big data technologies provided enterprises with the capacity to collect large volumes of information on customer behaviours, preferences, and feedback in real time. Advanced analytical tools then processed this data for patterns and trends that allowed much finer-grained segmentation. This meant that SMEs, even with their limited resources in emerging markets, were able to develop a deep understanding of their customer base and customise their offers to meet very specific needs. According to E. Genc *et al.* (2019), this approach will not only enhance competitiveness, but also enable dynamic segmentation adapted to market changes.

Customer behaviour analysis helps SMEs understand not only who their customers are, but how they interact with products and services. This can include purchasing patterns, brand interactions, and even social media behaviour, which was often overlooked in conventional segmentation models. Customer preference analysis will allow businesses to track changing tastes and preferences over time, providing a dynamic segmentation model that evolves with the market. The data from big data helps to analyse feedback through online reviews, surveys, and comments about services on social media, serving first-hand insights into customer satisfaction and areas needing change. The purpose of this study was to fill the research gap by providing a practical and scalable solution for SMEs in emerging markets to improve their market segmentation decisions.

## Literature Review

Market segmentation decisions are those in which a broad market is divided into distinct subsets of customers with common needs, characteristics, or behaviours, and then targeted with an appropriate marketing strategy. According to Y. Cui *et al.* (2025), preference-guided segmentation models addressed heterogeneous customer decision-making, allowing companies to make closer-to-accurate predictions of various customers' behaviours and optimise marketing strategies accordingly.

A. Aouad *et al.* (2023) indicated the development of SMEs, which were considered as a new approach for integrating segmentation with response modelling by offering computationally efficient and interpretable frameworks for segmenting large data.

Customer insights can be defined as understanding customer behaviours, preferences, and feedback, which can then be used from data to drive business strategy. According to B.M. Omowole *et al.* (2024), big data offered scalable solutions for the competitive advantage of SMEs by means of strategies pertaining to the analysis of customer behaviour and preferences. Y. Zhong *et al.* (2024) have shown how big data can be used to improve customer satisfaction by leveraging online reviews in refining service offers, especially for tourism industries.

The integration of customer insights from big data into market segmentation decision-making enables businesses to target their customers with unprecedented accuracy. According to X. Li & Y.S. Lee (2024), big data allowed companies to move beyond static demographic or geographic segmentation by integrating real-time behavioural and preference data into their segmentation models. This helped in the development of customised marketing strategies that will lead to more satisfaction and loyalty among customers. According to Z. Zhang (2024), neural network-based models played a crucial role in evaluating segmentation and marketing strategies, showing how these technologies will help to optimise segmentation for better results.

Customer behaviour analysis helped to identify the patterns and every step involved in reaching purchasing decisions. According to S. Garg & A. Khandhar (2024), consumer behaviour analysis indeed provided an opportunity to improve businesses through adjustments of market strategies with data-driven insights on purchasing trends and spending patterns. The relationship between behaviour analysis and market segmentation was implemented through the identification of different behavioural trends across various segments of customers. R.Y. Daulay *et al.* (2024) indicated that preference analysis played a significant role in the identification of customer personas and the elaboration of corresponding marketing strategies; this may refer to the use of K-Means clustering to segment consumers of the coffee shop market by lifestyle, preference, and purchasing behaviour.

Customer feedback analysis is the process of systematic collection and analysis of customer opinions, reviews, and experiences about a product or service. Through the identification of common themes in customer feedback, businesses can address pain points and refine product offerings to improve customer satisfaction and loyalty. A. Gopakumar *et al.* (2024) noted that the integration of consumer behaviour analysis with clustering algorithms was very important to enhance segmentation strategy in both e-commerce and conventional retail settings. According to Z. Samira *et al.* (2024), CRM (Customer Relationship Management) integrated with

AI-driven tools helped SMEs to optimise their marketing strategies for better customer interaction. The basic principle of CRM was that companies create more value for themselves, when they focused on customer retention rather than short-term sales, with customer insight driving personalisation and effective segmentation.

In the context of SMEs, CRM theory explained how data exploitation for increased customer insight would lead to more accurate market segmentation. D. Gamba (2022) explained that service-oriented segmentation models allowed the SME to filter out only the profitable clusters of customers, achieve resource optimisation, and adapt to operational barriers. A. Singh *et al.* (2024), investigated machine learning methods, which used to develop a market segmentation model using K-Means clustering and a consumer behaviour prediction model using a Random Forest from large-scale e-commerce datasets. The Random Forest model was much better in predicting customer habits in contrast to the K-Means clustering model. The study included precision, recall, and F1 scores as assessment criteria. According to the findings, machine learning techniques will be useful in market analysis, and businesses may utilise this model to create efficient marketing plans and comprehend customer behaviour.

K. Kumar *et al.* (2025) investigated the characteristics that determine customer preference for OTT (Over the Top) video streaming. Logistic regression was applied to the multivariate analysis of survey data affordability, quality, and accessibility have emerged as crucial factors affecting preference. Demographic data also played an important role in subscription decisions. M.M. Ibrahim & H.A. Mamdouh (2025) investigated the influence of online customer reviews on consumer buying decision. The methodological approach included a quantitative online survey conducted in Egypt, focusing on OCR (Online Customer Reviews) dimensions such as valence and volume. The findings indicated that online reviews have an immense impact on purchasing decisions, though moderated by demographics. However, no evidence has been observed linking customer feedback with market segmentation. It was concluded that though OCRs impact purchasing decisions, its usefulness in market segmentation requires more research.

## Materials and Methods

The research questions derived from the specific study objectives led to the use of a quantitative research design, which used a survey technique. The main questions were: 1) how does customer behaviour analysis affects market segmentation decisions; 2) in what ways does customer preference analysis affect market segmentation decisions; 3) what is the effect of customer feedback analysis on market segmentation decisions. This meant that via surveys, numerical data was collected from small business owners to understand how they use customer data for market segmentation. This design was chosen

because it allowed gathering specific, measurable information from many SME owners and analysing it statistically to draw reliable conclusions about how big data insights influenced their market segmentation decisions (Ragab & Arisha, 2018).

Selection consisted of 1,628 registered SME owners in Kwara State, Nigeria, who maintained customer databases and have defined market segments. The 2023 dataset of registered SMEs maintained by the Ministry of Commerce & Co-Operatives (2025) provided this figure. These SMEs were selected because they reflected companies that actively participate in official market segmentation procedures and keep track of consumer data. To determine the sample size, the study used T. Yamane's (1969) equation for finite population:  $n = N/(1 + N(e)^2)$ , where:  $n$  – sample size;  $N$  – population size (1,628);  $e$  – margin of error (0.05);  $n = 1,628/(1 + 1,628(0.05)^2)$ ;  $n = 1,628/5.07$ ;  $n = 321$  respondents. To account for potential non-responses, the sample size was increased by 10%, resulting in 353 respondents. The study employed a systematic random sampling technique, where every fifth SME owner from the alphabetically arranged list of 1,628 eligible SMEs was selected. This method ensured unbiased selection, while maintaining representativeness across different business sectors and sizes. The systematic approach provided a structured way of selecting participants, while maintaining randomness.

The unit of inquiry was individual SME owners or managers who: 1) have registered businesses in Kwara State; 2) maintained customer databases with at least one year of data; 3) have implemented some form of market segmentation in their business operations. This specific focus ensured that respondents have relevant

experience with both data management and market segmentation practices. The unit of analysis was the individual SME owner's responses regarding their use of customer data insights for market segmentation decisions. This included their practices in data collection, analysis methods, and how they applied these insights to segment their markets and make business decisions. A structured questionnaire was used, divided into sections covering demographics, customer insight, and market segmentation decisions. The questionnaire employed a 5-point Likert scale ranging from "Strongly disagree" (1) to "Strongly agree" (5).

Partial Least Squares Structural Equation Modelling (PLS-SEM) using SmartPLS v3.2.9 was employed for data analysis. It was used to examine the measurement model and structural model of the study data. Content validity was established through expert review by three business management professors and two SME consultants. Construct validity was assessed through convergent validity (AVE >0.5) and discriminant validity (Fornell Larcker). Reliability was measured using composite reliability and Cronbach's Alpha (threshold >0.7). A pilot test with 35 SME owners (10% of sample size) was conducted to refine the instrument.

## Results and Discussion

The analysis began with an overview of the response rate to the administered questionnaire. A majority of participants provided complete and valid responses, ensuring a solid foundation for the study's findings. This strong level of engagement reflected the relevance and clarity of the research instrument. The subsequent analysis included descriptive statistics and tests of normality, offering deeper insight into the data distribution (Table 1).

**Table 1.** Questionnaire administered response rate

Validity	Frequency	Percentage	Valid percentage	Cumulative percentage
Fully submitted responses	254	71.9	71.9	71.9
Remaining sample size	99	28.1	28.1	100.0
Total	353	100	100	

**Source:** developed by the authors

Table 1 showed that 71.9% of respondents answered the questionnaire completely and accurately of which their responses were valid for this study. The high response rate helped to achieve reliable findings from

the study. The descriptive result, which showed the mean of the measures of the study in depicted in Table 2, also gave the standard deviation of the measures, the normality test, including the kurtosis and skewness.

**Table 2.** Descriptive analysis and normality test

	Mean	Standard deviation	Excess kurtosis	Skewness	Number of observations used
Customer behaviour analysis 1	3.236	1.383	-1.164	-0.305	254.000
Customer behaviour analysis 2	3.457	1.356	-0.928	-0.566	254.000
Customer feedback analysis 1	2.866	1.193	-0.873	-0.019	254.000
Customer feedback analysis 2	3.339	1.305	-1.022	-0.284	254.000
Customer preference analysis 1	3.433	1.290	-0.911	-0.450	254.000
Customer preference analysis 2	3.213	1.234	-0.730	-0.310	254.000

Table 2, Continued

	Mean	Standard deviation	Excess kurtosis	Skewness	Number of observations used
Market segmentation decision 1	3.780	1.380	-0.463	-0.900	254.000
Market segmentation decision 2	3.929	1.393	-0.118	-1.122	254.000
Market segmentation decision 3	3.874	1.403	-0.240	-1.065	254.000

Source: developed by the authors

The study considered market segmentation and customer insights. A number of important indicators were evaluated, each of which provided insight into a distinct facet of the market segmentation and consumer insights. The mean scores, standard deviations, and the number of observations used for each indicator provided valuable insights and implications for researchers and practitioners. The relatively high mean score, which were above 3 for the questions suggested that respondents perceive customer insights to be highly relevant to market segmentation decisions. With low standard deviation in each cases, indicating that there was low deviation of the responses from the mean. These descriptive results underscored the multifaceted nature of customer insights on market segmentation decisions. They emphasised the importance of market segmentation decisions through successful customer insights.

The normality results of the distribution revealed that the sample size was above 100, which implied that an absolute value of skewness of +1.0 or below was expected for the data to be normal. In addition, for

kurtosis, an absolute value of  $\pm 3.0$  was expected for a normal peak, as any value outside the threshold could be a serious signal of concern. The normality results showed that all the variables were within the threshold of the absolute value of  $\pm 1.0$  and the kurtosis results were also within the absolute value of  $\pm 3.0$ . The implication from the normality test results showed that all the data inputted for the analysis were normally distributed and can be used for further analysis and inferences. This implied that all the variables used to measure resource optimisation have moderate mean with low deviation from the mean and the variables were all normally distributed indicating the usefulness of the variables in determining the causality between customer insights and market segmentation decisions. For this, the variables used to measure customer insights were customer behaviour analysis, customer preference analysis, and customer feedback analysis against market segmentation decisions. Figure 1 showed the structural path model that assesses the effect of customer insights on market segmentation decisions.

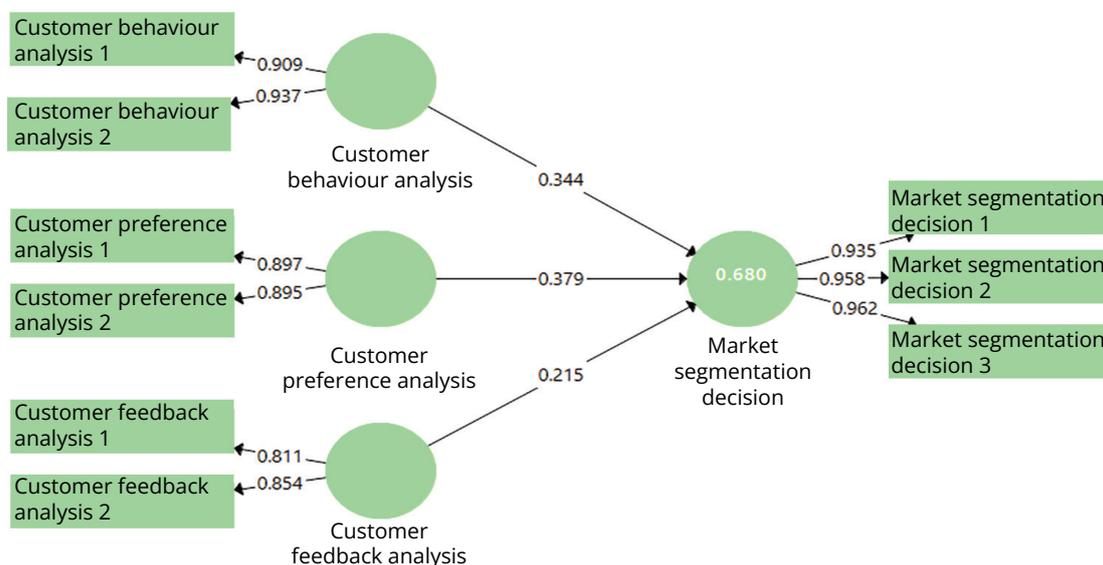


Figure 1. Model of the path to customer insights and market segmentation decision

Source: developed by the authors

Three independent variables – analysis of consumer behaviour, preferences, and feedback – and one dependent variable – choice to segment the market were included in the model. According to the model's findings, market segmentation decisions were significantly

influenced favourably by all three independent factors. This indicated that organisations should value consumer insights since they can aid in making better market segmentation decisions. The particular impacts demonstrated that every independent variable significantly

influences the choice to segment the market. This implied that in order to improve market segmentation decisions, organisations should concentrate on creating

consumer insights. Important statistical indicators pertaining to the validity and construct reliability of the four latent variables in this study were shown in Table 3.

**Table 3.** Construct reliability and validity

	Cronbach's Alpha	Composite reliability	Average Variance Extracted (AVE)
Customer behaviour analysis	0.828	0.920	0.852
Customer feedback analysis	0.759	0.819	0.693
Customer preference analysis	0.754	0.891	0.803
Market segmentation decision	0.948	0.966	0.905

**Source:** developed by the authors

These metrics aid in evaluating how well these variables quantify the fundamental ideas they are meant to reflect. Cronbach's Alpha and composite dependability were the two main measures used to assess construct dependability. Cronbach's Alpha assesses a latent variable's internal consistency by determining the extent to which each item was related to every other item. Good quality was shown by the internal consistency scores of the four latent variables, which were above 0.7. Since these values were far higher than the widely accepted cut off limit of 0.7, they suggested that the items within each variable were reliable markers of the related structures. Composite reliability was another construct reliability statistic that considered both internal consistency and the relationships between the items and the latent variable. All of the variables in this study showed strong composite dependability, providing a more trustworthy measure of reliability, with all values over 0.7. The latent variables' high values suggested that they were trustworthy predictors of the constructs they stand for.

Table 3 also displayed the Average Variance Extracted (AVE), which evaluated each latent variable's convergent validity. The degree to which items in a variable measure the same underlying notion and were connected to one another was known as convergent validity. All of the AVE values in the table were higher than the suggested cut off of 0.5. This suggested that each latent variable's items were converging nicely and measuring their respective constructs as a whole. The choice of these variables as valid and dependable measures in the study was supported by their strong composite reliability, high internal consistency, and good convergent validity (Osei *et al.*, 2024). Strong evidence of discriminant validity among the latent variables – customer feedback analysis, customer behaviour analysis, market segmentation decision, and customer preference analysis – was shown by the findings of the discriminant validity study in Table 4. Whether these constructs were separate and not strongly associated with one another was determined by discriminant validity.

**Table 4.** Discriminant validity

	Customer behaviour analysis	Customer feedback analysis	Customer preference analysis	Market segmentation decision
Customer behaviour analysis	<b>0.923</b>			
Customer feedback analysis	0.723	<b>0.833</b>		
Customer preference analysis	0.642	0.601	<b>0.896</b>	
Market segmentation decision	0.743	0.691	0.729	<b>0.952</b>

**Source:** developed by the authors

It was clear from examining the correlations between these variables that the off-diagonal values – the correlations between other variables – were significantly lower than the diagonal values, which represent the correlations of each variable with itself. This supported the notion that each latent variable was unique and measures a separate feature of the overall construct by indicating that each latent variable has a stronger relationship with itself than with the other constructs. Compared to its correlations with customer behaviour, customer feedback, and customer preference analysis, the market segmentation decision has a stronger connection with itself. In a similar vein, the connection between customer preference analysis and itself was stronger than that between the other factors. However, this was

also true for other variables in their own contexts. These findings demonstrated that rather than being merely various expressions of the same underlying construct, the latent variables in this study were measuring unique ideas. Given that it successfully distinguished between these crucial elements – customer feedback analysis, customer behaviour analysis, market segmentation decision, and customer preference analysis – it appeared that the measurement model was appropriate for the goals of this investigation.

This allowed evaluating the independent variable's correlation. The purpose was to determine, whether two independent variables were not associated and yielding same results. In this study, the expected association between the independent variables was evaluated using

the variance inflation factor (VIF). The VIF values for the latent variables pertaining to the choice of market segmentation were shown in Table 5. Customer feedback, customer behaviour, and consumer preference analysis all have VIF values that were much below the 10-point cut off, which was encouraging. It implied that these la-

tent variables do not exhibit significant multicollinearity. Since there was little correlation between these variables, multicollinearity was not a major problem, when they were included in this study. The coefficient of determination, or R-squared, which is a measure of a model's quality of fit, was displayed in Table 6.

**Table 5.** Inner VIF values

	Customer behaviour analysis	Customer feedback analysis	Customer preference analysis	Market segmentation decision
Customer behaviour analysis				2.444
Customer feedback analysis				2.246
Customer preference analysis				1.822
Market segmentation decision				

**Source:** developed by the authors

**Table 6.** Coefficient of determination score

	R-square	R-square adjusted
Market segmentation decision	0.680	0.676

**Source:** developed by the authors

Approximately 68.0% of the variability seen in the dependent variable (market segmentation decision) can be explained by the independent or latent variables included in the model, according to the market segmentation decision model's R-squared score of 0.680. This suggests that the model captures and explained the observed variations in the buying experience. The corrected R-squared value was 0.676. This results in a more careful evaluation of the model's degree of fit. The modified R-squared value was almost the same as the conventional R-squared value, indicating that the inclusion of the independent variables in the model was unlikely

to cause overfitting or excessive complexity. This implied that even when considering any problems relating to model complexity, the explanatory power of the model was still strong. According to the R-squared and modified R-squared values, the market segmentation decision model explained market segmentation decision variability rather well, and adding more latent variables does not seem to degrade the model's performance. In statistical analysis, the effect size, which was commonly represented as f-square and shown in Table 7, quantified the strength of the correlation or influence of independent variables on a dependent variable.

**Table 7.** Assessment of the effect size ( $f^2$ )

	Customer behaviour analysis	Customer feedback analysis	Customer preference analysis	Market segmentation decision
Customer behaviour analysis				0.152
Customer feedback analysis				0.064
Customer preference analysis				0.246
Market segmentation decision				

**Source:** developed by the authors

It evaluated the impact sizes of several latent factors on market segmentation decision. Every independent variable had a value greater than 0.02, which was regarded as a minor effect size. This implied that every variable had a moderate effect size, meaning that each one had a discernible influence on the choice to

segment the market. Variability in market segmentation decisions can be moderately explained by changes or variations in any of the factors. The null hypothesis that customer insights have no discernible impact on market segmentation decisions was tested using the bootstrap route coefficient analysis shown in Table 8.

**Table 8.** Bootstrapping results showing path coefficient for structural model

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T-statistics ( O/STDEV )	P-values
Customer behaviour analysis -> Market segmentation decision	0.344	0.346	0.075	4.608	0.000
Customer feedback analysis -> Market segmentation decision	0.215	0.213	0.068	3.155	0.002

Table 8, Continued

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T-statistics ( O/STDEV )	P-values
Customer preference analysis -> Market segmentation decision	0.379	0.379	0.057	6.654	0.000

**Source:** developed by the authors

According to the findings, market segmentation decisions were significantly impacted by customer feedback, customer behaviour, and consumer preference analyses as components of customer insights. An examination of the sequence from Customer feedback, customer behaviour, and customer preference analysis to the decision about market segmentation reveals a statistically significant relationship between these three types of analysis and the decision to segment the market. Strong evidence to reject the null hypothesis was suggested by the t-statistics being more than 1.96 and the p-values being less than the traditional significance level of 0.05. As a result, the choice to segment the market was greatly influenced by the characteristics of consumer insights; customer feedback, customer behaviour, and customer preference.

The study determined the effect of customer insights on market segmentation decisions, with the hypothesis being that customer insights do not significantly affect market segmentation decisions. The results revealed that all three factors; customer feedback analysis, customer behaviour analysis, and customer preference analysis, have statistically significant effects on market segmentation decisions. This finding aligned with O.R. Amosu *et al.* (2024), who demonstrated that real-time data analytics provides strategic customer insights crucial for effective e-commerce segmentation. Similarly, M.E. Jalal & A. Elmaghraby (2024) found that counterfactual analysis offered a new perspective on personalised marketing, enabling more precise customer segmentation. S. Park *et al.* (2024) supported this finding through their importance-induced customer segmentation approach using explainable machine learning, which enhanced the accuracy of market segmentation decisions. These studies collectively emphasised, how modern analytical techniques transformed customer insights into actionable segmentation strategies.

The rejection of the null hypothesis was further supported by both historical and contemporary research. F. Qian (2008) established a foundational understanding of CRM and customer segmentation outsourcing for small and medium businesses, highlighting the long-standing importance of customer insights in segmentation. More recently, B.S.V. Reddy *et al.* (2023) demonstrated the effectiveness of clustering algorithms in customer segmentation analysis, providing technical validation for the relationship between customer insights and segmentation decisions. L. Sanu (2024) presented a practical application through Reliance Jio's customer analytics platform, showing how big data can be collected for

meaningful customer insights that drive segmentation strategies. D.K. Sharma & M. Kumar (2023) contributed methodological rigour through their market segment evaluation using grey relational analysis, demonstrating quantitative approaches to translate customer insights into segmentation decisions.

The comprehensive effect of customer insights on market segmentation was contextualised by P. Singh *et al.* (2023), who provided an integrative review of consumer behaviour in the service industry, establishing the theoretical foundation for why customer insights matter in segmentation decisions. The findings of this study were also consistent with the results of M.K. Chaudhary *et al.* (2024), who found customer behaviour to be vital marketing concept, M. Deng (2024) focused on customer profiling for market segmentation, and M.M. Ibrahim & H.A. Mamdouh (2025), who demonstrated that utilising customer insights through advanced analytics enabled businesses to create more precise customer profiles, leading to more effective segmentation strategies. Through leveraging these multi-dimensional customer insights, organisations can develop highly targeted marketing approaches that addressed specific customer needs, significantly improving engagement and conversion rates. This data-driven approach to segmentation allowed for continuous refinement and adaptation to changing market conditions, ensuring sustainable competitive advantage in increasingly dynamic business environments.

## Conclusions

In the dynamic landscape of emerging markets, small and medium-sized enterprises in Kwara State, Nigeria, have discovered the transformative power of data-driven market segmentation. Research has highlighted the critical role of customer insights derived from big data analytics in shaping strategic business decisions.

The comprehensive analysis in the study revealed three pivotal factors of customer insights that significantly impact market segmentation: customer feedback analysis, customer behaviour analysis, and customer preference analysis. These dimensions provided SMEs with a nuanced understanding of their target markets, enabling more precise and effective strategic positioning. Businesses may gain numerous significant benefits by collecting and analysing client data in a systematic manner. First, it was determined how to design highly focused marketing tactics that resonate with certain client categories. This approach allowed for more personalised product offerings and

communication, which directly addressed the unique needs and preferences of different customer groups. The normality test results indicated that all variables fell within acceptable thresholds for skewness ( $\pm 1.0$ ) and kurtosis ( $\pm 3.0$ ), confirming a normal distribution of the data. This validated the reliability of the variables used to measure resource optimisation and supported their suitability. Customer insights can be effectively used to assess their influence on market segmentation decisions. SMEs in emerging markets should enhance market segmentation by leveraging customer feedback, behaviour, and preference analysis through tools like surveys, CRM systems, and social media analytics to inform targeted marketing strategies.

Moreover, the research underscored the potential for improved customer satisfaction and loyalty through data-driven insights. SMEs that leveraged these analytical approaches can develop a more intimate

understanding of their customer base, anticipating needs and adapting their strategies proactively. This was particularly crucial in emerging markets, where customer expectations and market dynamics were rapidly evolving. The findings presented a compelling argument for investment in data analytics capabilities, positioning customer insights as a critical competitive advantage for SMEs seeking to ensure long-term expansion in a challenging market environment.

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### Conflict of Interest

None.

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## Використання big data для розуміння споживачів і сегментації ринку МСП у країнах, що розвиваються

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**Анотація.** Малі та середні підприємства у всьому світі, особливо в країнах з економікою, що розвивається, стикаються з викликами у процесі сегментації ринку. Вони мають обмежене уявлення про важливість отримання інсайтів про споживачів із великих даних для прийняття обґрунтованих рішень щодо сегментації ринку. Метою цього дослідження було оцінити роль здобуття споживчих інсайтів із великих даних у прийнятті рішень щодо сегментації ринку малих та середніх підприємств в умовах економік, що розвиваються. Результати дослідження засвідчили, що аналіз споживчої поведінки суттєво впливає на рішення щодо сегментації ринку серед малих і середніх підприємств. Значення  $\beta$ -коефіцієнта становило 0,344, що свідчило про те, що одинична зміна в аналізі споживчої поведінки зумовлює відповідну зміну в рішеннях щодо сегментації ринку, при  $t$ -статистиці 4,608 та  $p$ -значенні 0,001. Було також встановлено, що аналіз споживчих переваг має значний вплив на сегментаційні рішення малих та середніх підприємств. Значення  $\beta$ -коефіцієнта становило 0,379, що вказало на сильну залежність між змінами в аналізі переваг споживачів та рішеннями щодо сегментації ринку, при  $t$ -статистиці 6,654 та  $p$ -значенні 0,001. Крім того, результати дослідження показали, що аналіз зворотного зв'язку від споживачів також істотно впливає на рішення щодо сегментації ринку серед малих та середніх підприємств. Значення  $\beta$ -коефіцієнта дорівнювало 0,215, при  $t$ -статистиці 3,155 та  $p$ -значенні 0,002. Зроблено висновок, що отримання інсайтів про споживачів із великих даних є важливим чинником для малих і середніх підприємств в економіках, що розвиваються, у процесі прийняття ефективних рішень щодо сегментації ринку.

**Ключові слова:** складні дані; аналіз споживчої поведінки; аналіз відгуків споживачів; споживча перспектива; аналіз споживчих переваг