



Effect of Digital Sensing Capability on Competitive Advantage of Commercial Banks in Kenya

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Abstract

The purpose of the study was to examine the relationship between digital sensing capability and competitive advantage among commercial banks in Kenya. The study adopted a post-positivist research philosophy and an explanatory research design anchored on Dynamic Capabilities Theory. The target population consisted of 370 respondents drawn from the 37 commercial banks in Kenya. Stratified random sampling was employed to select 192 respondents, comprising Chief Executive Officers and Heads of key departments, including finance, marketing, human resource, strategy, customer relations, operations, credit, information and communication technology, risk and compliance, and internal audit. Primary data were collected using a self-administered questionnaire and analysed using descriptive and inferential statistics with the Statistical Package for the Social Sciences (SPSS) version 25. Descriptive statistics included frequencies, means, and standard deviations, while ordinal logistic regression was used for hypothesis testing. Digital Sensing Capability was positively and significantly associated with higher Competitive Advantage ($\beta = 6.932$, $SE = 0.817$, $Wald = 71.988$, $p < .001$). The Nagelkerke Pseudo R^2 was 0.749, indicating a substantial improvement in model fit relative to the intercept-only model. This value is reported as a pseudo- R^2 index and is not interpreted as a percentage of variance explained, because pseudo- R^2 does not have the same meaning as R^2 in ordinary least-squares regression. Higher Digital Sensing Capability was associated with greater odds of higher Competitive Advantage. Commercial banks should continuously strengthen digital infrastructure, monitor customer behaviour and fintech developments, and use market intelligence to anticipate emerging opportunities and threats. Consistent with Dynamic Capabilities Theory, continually renewing digital sensing capabilities enables banks to adapt rapidly and sustain competitive advantage. Managers should implement structured digital sensing frameworks that integrate market, technology, and internal sensing into strategic planning to enhance competitive advantage among commercial banks in Kenya.

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Introduction

Commercial banks operate in a highly dynamic and competitive financial market environment. They face stiff competition as they strive to provide financial services (Srivastava, Singh & Jain, 2023). The liberalisation of financial markets has led to an increase in the number of institutions offering similar



financial products and services (King'oku & Muathe, 2024). Additionally, deregulation, and privatisation changes have intensified competition within the sector and brought external competitors, primarily non-banking financial institutions and market-based financing options. Equally, the shifting interest rate cycle has forced banks to compete in a new landscape, where they have to continue focusing on transforming their business models to maintain revenue growth and profitability. The main drive for the Banks is to remain competitive in the ever-dynamic market.

A firm's competitive advantage refers to the attributes that enable it to outperform competitors by creating superior value for customers through lower costs, differentiated products, or unique services (Khalaf, Hammood, & Issa, 2024). Sustaining competitive advantage is essential for long-term business success despite increasing competition. Competitive advantage can be viewed from two dimensions: efficiency advantage, where firms operate more efficiently than competitors, and value advantage, where firms deliver greater customer value that justifies higher prices (Farhikhteh & Farhikhteh, 2024). According to Farida and Setiawan (2022), organisations achieve competitive advantage through cost leadership or differentiation strategies that enhance customer value and strengthen market position.

Sensing capabilities refer to a firm's ability to perceive, identify, and interpret signals from both internal and external environments (Engelmann, 2023). They enable organisations to capture new opportunities, foresee potential threats, and adjust their strategies accordingly (Bornay-Barrachina et al., 2025). Digital sensing capability, which enables banks to systematically identify and interpret emerging market opportunities, technological developments, changing customer needs, and internal organisational changes, is considered a critical driver of competitive advantage (Bornay-Barrachina et al., 2025). In this study, digital sensing capability is conceptualised as a multidimensional construct comprising market sensing, technology sensing, and internal sensing. Market sensing enables banks to detect shifts in customer preferences, competitor actions, and emerging market opportunities; technology sensing facilitates the identification and assessment of emerging digital technologies and technological trends; while internal sensing enables banks to recognise changes in internal capabilities, processes, resources, and organisational needs (Khalaf et al., 2024).

Although digital technology adoption presents a practical business challenge, the deeper academic problem concerns the limited understanding of how banks in Sub-Saharan Africa develop and deploy digital sensing capabilities within resource-constrained and rapidly changing institutional environments (Chingufo et al., 2026; Israel & Mwenda, 2024). Existing Dynamic Capabilities literature largely conceptualises sensing as a general organisational capability, with limited attention to how its market, technology, and internal dimensions operate within commercial banking in Kenya. Consequently, the literature provides insufficient empirical explanation of how Kenyan banks transform digital resources and environmental information into competitive advantage through context-specific sensing capabilities.

The Central Bank of Kenya's Banking Sector Innovation Survey (2024) reports that 98% of commercial banks have adopted mobile banking, 79% utilise application programming interfaces (APIs), 42% have implemented cloud computing, and 40% use biometrics and big data analytics. Despite these substantial investments in digital technologies, many banks continue to experience limited improvements in market share, customer loyalty, and operational efficiency, suggesting that technology adoption alone does not guarantee sustained competitive advantage. This highlights a potential gap between digital technology resources and digital sensing capability. While digital technologies provide infrastructure, data, and technological resources, digital sensing capability enables banks to identify and interpret emerging market opportunities, technological developments, customer needs, and internal changes. The critical issue, therefore, is whether banks can effectively



leverage digital resources through sensing capabilities to translate technological investments into sustained competitive advantage within the Kenyan banking context.

Empirical evidence generally suggests that digital sensing capability enhances competitive advantage. Ferreira et al. (2020) and Xie and Wang (2023) found that strong sensing capabilities enable organisations to anticipate technological and market changes, identify emerging opportunities, and respond strategically, thereby strengthening competitiveness. However, empirical evidence on the specific contribution of digital sensing capability to competitive advantage remains limited in the commercial banking sector, particularly in Kenya and the broader East African context. Moreover, most previous studies have examined digital transformation as a broad construct, providing limited insight into the distinct role of digital sensing capability. This contextual and construct-specific empirical gap justifies the present study.

Theoretical Review

Dynamic Capability Theory (DCT), developed by Teece, Pisano, and Shuen (1997) and further elaborated by Teece (2007), provides the theoretical foundation for this study. DCT explains how firms sustain competitive advantage in dynamic environments through capabilities that enable them to sense opportunities and threats, seize opportunities, and transform or reconfigure resources. The theory distinguishes dynamic capabilities from ordinary operational capabilities because they enable organisations to adapt their resource base in response to environmental changes. Sensing involves identifying and interpreting emerging opportunities and threats; seizing involves mobilising resources to capture identified opportunities; while transforming entails reconfiguring organisational resources and capabilities to maintain competitiveness (Teece, 2007). Thus, DCT provides a suitable lens for understanding digital sensing capability as an important organisational capability.

Although DCT encompasses sensing, seizing, and transforming, this study deliberately focuses on sensing capability as the primary gatekeeper process. Sensing precedes seizing and transformation because organisations must first identify and interpret environmental changes before determining appropriate responses or reallocating resources. Digital sensing capability therefore provides the intelligence foundation upon which subsequent dynamic capability processes depend. Consistent with Pavlou and El Sawy (2011), this study conceptualises digital sensing capability through market sensing, technology sensing, and internal sensing, enabling commercial banks to detect changes in customer needs, technologies, markets, competitors, and internal conditions. The study does not suggest that sensing alone represents the complete dynamic capability process; rather, it examines whether this upstream capability is directly associated with competitive advantage among commercial banks in Kenya.

Conceptual Framework

Figure 1 presents the study's conceptual framework and illustrates the relationship between the independent and dependent variables. The independent variable is digital sensing capability, while the dependent variable is the competitive advantage of commercial banks in Kenya.

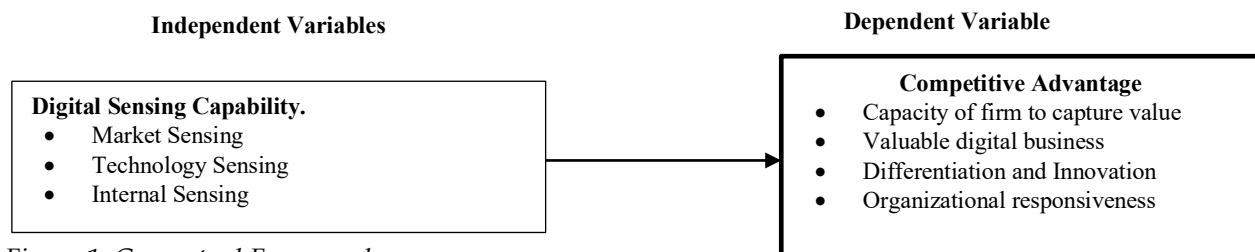


Figure 1: Conceptual Framework



Literature Review

Sudrajat et al. (2019) found that sensing capability had a positive and statistically significant effect on innovative logistics services, which subsequently enhanced financial performance. Similarly, Wong and Ngai (2025) established that analytics capability and sensing capability significantly influenced operations performance. Ojo (2025) further found that sensing capabilities significantly contributed to the growth performance of MSMEs in Nigeria, highlighting the role of organisational capabilities in responding to changing market conditions. In Kenya, Ng'ang'a et al. (2024) established a significant relationship between sensing capabilities and the performance of supermarkets, while Bett and Anene (2023) found that sensing capabilities significantly influenced the performance of small and medium agrifood enterprises in Nairobi County. Indeje and Mutua (2024) similarly reported that sensing capabilities significantly influenced competitive advantage in Kenya's telecommunication industry. These findings collectively demonstrate that sensing capabilities enable organisations to identify opportunities, respond to environmental changes, improve performance, and strengthen competitive positioning. However, empirical evidence on the direct effect of digital sensing capability on the competitive advantage of commercial banks in Kenya remains limited. Therefore, this study tested the following null hypothesis:

H0: Digital sensing capability has no statistically significant effect on the competitive advantage of commercial banks in Kenya.

Method

Research Philosophy and Design

This study adopted the post-positivist research philosophy, which supports objective and empirical investigation through quantitative methods, measurement, and hypothesis testing (Creswell & Creswell, 2022). An explanatory research design was employed to examine the association between Digital Sensing Capability and Competitive Advantage among commercial banks in Kenya (Saunders et al., 2019). The design was appropriate for assessing the extent to which variations in Digital Sensing Capability were associated with differences in Competitive Advantage and for testing the hypothesised relationship. Given the cross-sectional and single-source nature of the data, the findings are interpreted as explanatory associations rather than causal effects.

Target Population and Sampling Technique

The target population consisted of 370 respondents drawn from CEOs and heads of key departments, including finance, marketing, human resource, strategy, customer relations, operations, credit, ICT, risk and compliance, and internal audit, across the 37 commercial banks in Kenya. The inclusion of these management positions was based on their direct involvement in strategic decision-making and their knowledge of digital sensing capability and competitive advantage within their respective banks. The study employed stratified random sampling, a probability sampling technique in which the population is divided into homogeneous subgroups (strata) based on characteristics relevant to the research (Hall, 2020). The respondents were organised into strata according to their functional roles across the 37 commercial banks licensed by the Central Bank of Kenya, after which respondents were randomly selected from each stratum. The study used Yamane's (1967) simplified formula to calculate a sample size of 192 respondents, which provided the required number of target responses. The distribution of the sample size was as presented in Table 1.

*Table 1: Sample Size Proportion*

Stratum	Target Population	Sample Size
CEO	37	19
Finance	37	19
Marketing	35	18
Human Resource	37	19
Strategy	25	13
Customer Relations	37	19
Operations	29	15
Credit	36	19
Information and Communication Technology	36	19
Risk and Compliance	34	18
Internal Audit	27	14
Total	370	192

Data Collection and Data Analysis Methods

For this study, primary data was collected using structured questionnaires administered to CEOs and heads of departments. Quantitative data analysis was used to analyse numbers rather than words. Questionnaire data were edited, coded, and entered into SPSS Version 25 for analysis, with incomplete responses excluded. Descriptive and inferential statistics were then generated to address the study objectives and test the hypotheses. Descriptive statistics (frequencies, means, and standard deviations) were used to summarise respondents' responses, while inferential statistics comprising factor analysis and ordinal logistic regression were used to test the study hypotheses and determine relationships among the variables. The suitability of the data for factor analysis was assessed using the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity.

The study applied Ordinal Logistic Regression (OLR) to test the hypotheses because Competitive Advantage was measured using a five-point Likert scale, producing ordered response categories ranging from lower to higher levels of competitive advantage. The ordinal nature of the response categories made OLR appropriate for estimating the effect of digital sensing capability on the likelihood of attaining a higher level of competitive advantage without assuming equal distances between the response categories. Model adequacy was assessed using the Model Fitting Information and Nagelkerke Pseudo R^2 , while the Parameter Estimates were used to determine the significance, direction, and magnitude of the relationships between the predictor and the ordered levels of competitive advantage. The results were reported using the Beta coefficient (β) and Standard Error (SE) to evaluate the estimated effects and their statistical significance.

Results

The study initially targeted a sample of 192 respondents drawn from CEOs and heads of key departments, including finance, marketing, human resource, strategy, customer relations, operations, credit, information and communication technology (ICT), risk and compliance, and internal audit across all 37 licensed commercial banks in Kenya, as provided by the Central Bank of Kenya (2024). Of the 192 questionnaires distributed, 183 were duly completed and returned, yielding an overall response rate of 95.31%. Thus, the final sample used for data analysis comprised 183 respondents. According to Connaway and Powell (2010, p. 18), a response rate of 75% or higher is considered adequate for data analysis, drawing conclusions, and making recommendations. Therefore, the achieved response rate of 95.31% was considered highly sufficient for the study, providing an adequate basis for the subsequent statistical analyses and interpretation of the findings.

As illustrated in Table 2, 41.5% of the respondents were aged between 35 and 44 years, 32.8% were between 45 and 54 years, 15.8% were aged 55 years and above, while 9.8% were aged between 25 and 34 years. This indicates that the majority of respondents were in the 35 to 44 years' age bracket,



suggesting a mature and experienced cohort with the capacity to provide informed insights relevant to the study variables.

Regarding position in the organisation, the largest proportion of respondents (10.4% each) were drawn from head of finance, head of human resource, head of customer relations, head of ICT, and head of credit roles. Other positions, including head of marketing and head of risk and compliance (9.8% each), head of operations (8.2%), head of internal audit (7.7%), head of strategy (7.1%), and CEO (5.5%), contributed varying proportions of the respondents. This distribution demonstrates that the study captured perspectives from a wide range of functional areas, ensuring diverse input from key operational and strategic roles within the organisation.

In regard to duration of work, 39.3% of the respondents reported having 11–20 years of work experience, followed by 30.6% with 6–10 years, 18.0% with 21–30 years, 6.0% with less than 5 years, and 6.0% with over 30 years of experience. This indicates that the majority of respondents have between 6 and 20 years of professional experience, suggesting a workforce with substantial expertise and familiarity with organisational processes, which enhances the reliability and depth of insights provided for the study.

As demonstrated in Table 2, the majority of respondents (47.5%) held a Master's degree, followed by 27.3% with a Doctoral degree, and 25.1% with a Bachelor's degree. This indicates that most participants possessed advanced academic qualifications, reflecting a highly educated managerial cohort capable of providing informed and reliable insights relevant to the study.

Table 2: Demographic Information

Demographic and Instruction Characteristics	Percent
Gender	
Male	54.1
Female	45.9
Age Bracket	
25 and 34 years	9.8
35 and 44 years	41.5
45 and 54 years	32.8
55 years and above	15.8
Position in the Organisation	
Head of Finance	10.4
Head of Human Resource	10.4
Head of Customer Relations	10.4
Head of ICT	10.4
Head of Credit role	10.4
Head of Marketing	9.8
Head of Risk and Compliance	9.8
Head of Operations	8.2
Head of Internal Audit	7.7
Head of Strategy	7.1
CEO	5.5
Duration of Work	
Below 5 years	6
6–10 years	30.6
11–20 years	39.3
21–30 years	18
Over 30 years	6
Highest Education Level Attained	
Bachelor's degree	25.1
Master's degree	47.5
Doctoral degree	27.3



Descriptive Analysis for Competitive Advantage

Capacity of Firm to Capture Value

Respondents agreed that the organisation sustains value creation through digital initiatives ($M = 4.328$, $SD = 0.820$), followed by agreement that the bank maximises returns from digital transformation efforts ($M = 4.306$, $SD = 0.922$), and that the bank effectively captures value from its digital investments ($M = 4.262$, $SD = 0.817$). The respondents further agreed that systems are in place to convert digital capabilities into long-term competitive advantage ($M = 4.169$, $SD = 0.733$). Overall, the average mean ($M = 4.266$, $SD = 0.823$) indicates general agreement that digital initiatives enhance organisational performance, with moderate variability in respondents' perceptions regarding the organisation's ability to capture and maximise value from these initiatives.

Table 3: Descriptive Statistics for Capacity of Firm to Capture Value

Statements	N	Mean	Std. Dev
Our bank effectively captures value from its digital investments.	183	4.262	.817
The organisation has systems in place to convert digital capabilities into long-term competitive advantage.	183	4.169	.733
Our bank maximises returns from digital transformation efforts.	183	4.306	.922
The organisation sustains value creation through digital initiatives.	183	4.328	.820
Average		4.266	0.823

Valuable Digital Business

Respondents generally agreed that the bank offers digital products and services that are perceived as valuable by customers ($M = 4.279$, $SD = 0.787$). The respondents also agreed that the organisation has developed new business models enabled by digital technologies ($M = 4.219$, $SD = 0.875$) and that digital channels have expanded the bank's revenue streams significantly ($M = 4.175$, $SD = 0.927$). Overall, the average mean ($M = 4.224$, $SD = 0.863$) indicates general agreement that digital initiatives positively influence product and service value, business model innovation, and revenue growth, while the standard deviation reflects moderate variability in respondents' perceptions.

Table 4: Descriptive Statistics for Valuable digital business

Statements	N	Mean	Std. Dev
The bank offers digital products and services that are perceived as valuable by customers.	183	4.279	.787
Our organisation has developed new business models enabled by digital technologies.	183	4.219	.875
Digital channels have expanded the bank's revenue streams significantly.	183	4.175	.927
Average		4.224	0.863

Differentiation and Innovation

The respondents generally agreed that the organisation promotes a culture of innovation driven by digital initiatives ($M = 4.284$, $SD = 0.746$), followed by agreement that the organisation's use of digital technologies enhances product and service differentiation ($M = 4.219$, $SD = 0.816$) and that the bank leverages digital tools to offer unique services that stand out in the market ($M = 4.213$, $SD = 0.854$). The respondents further agreed that the organization is often the first-mover in adopting innovative digital banking solutions ($M = 4.197$, $SD = 0.952$). The standard deviations, ranging from 0.746 to 0.952, indicate moderate variability in responses, suggesting that while there is general agreement on the role of digital initiatives in promoting innovation and differentiation, perceptions vary more regarding first-mover adoption in the market.



Table 5: Descriptive Statistics for Differentiation and Innovation

Statements	N	Mean	Std. Dev
Our bank leverages digital tools to offer unique services that stand out in the market.	183	4.213	.854
The organisation promotes a culture of innovation driven by digital initiatives.	183	4.284	.746
Our bank's use of digital technologies enhances product and service differentiation.	183	4.219	.816
The organization is often the first-mover in adopting innovative digital banking solutions.	183	4.197	.952
Average		4.228	0.842

Organisational Responsiveness

As shown in Table 6, respondents generally agreed that the organisation demonstrates agility in adjusting digital processes to respond to external shifts ($M = 4.306$, $SD = 0.815$). The respondents also agreed that the organisation quickly responds to market changes using digital capabilities ($M = 4.202$, $SD = 0.810$) and that digital strategies are adapted in response to customer feedback and competitive trends ($M = 4.202$, $SD = 0.618$). In addition, the respondents agreed that the bank continuously evolves its digital services to meet changing customer demands ($M = 4.126$, $SD = 0.846$). Overall, the average mean ($M = 4.209$, $SD = 0.772$) indicates general agreement that the bank exhibits responsiveness and agility in its digital initiatives, while the standard deviation reflects moderate variability in perceptions across the different dimensions of adaptability and service evolution.

Table 6: Descriptive Statistics for Organisational Responsiveness

Statements	N	Mean	Std. Dev
Our bank quickly responds to market changes using digital capabilities.	183	4.202	.810
The organisation adapts digital strategies in response to customer feedback and competitive trends.	183	4.202	.618
Our bank continuously evolves its digital services to meet changing customer demands.	183	4.126	.846
The organisation demonstrates agility in adjusting digital processes to respond to external shifts.	183	4.306	.815
Average		4.209	0.772

Factor Analysis for Competitive Advantage

The Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy is 0.908, indicating a good level of suitability for factor analysis, as values above 0.6 are considered acceptable. This suggests that the sample size and correlations among variables are adequate for principal component analysis (PCA). Bartlett's Test of Sphericity is highly significant ($\chi^2 = 1646.675$, $df = 105$, $p < 0.001$), indicating that the correlation matrix is not an identity matrix and that significant relationships exist among the variables. This confirms that PCA can be meaningfully applied to the dataset.

Table 7: KMO and Bartlett's Test for Competitive Advantage

KMO and Bartlett's Test			
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.			.908
Bartlett's Test of Sphericity	Approx. Chi-Square		1646.675
	df		105
	Sig.		.000

Table 8 presents the Total Variance Explained for the 15 indicators of Competitive Advantage using Principal Component Analysis (PCA). The results show that the first principal component had an eigenvalue of 7.588 and explained 50.585% of the total variance, while the second component had an eigenvalue of 1.340 and accounted for an additional 8.934%, bringing the cumulative variance explained by the first two components to 59.518%. Although two components had eigenvalues greater than 1, the first component accounted for the largest proportion of the variance and explained more than half of the total variability in the 15 indicators. The substantial variance explained by the first



component indicates that the indicators were strongly concentrated around a dominant underlying dimension of Competitive Advantage.

Table 8: Total Variance Explained for Competitive Advantage

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	7.588	50.585	50.585	7.588	50.585	50.585
2	1.340	8.934	59.518	1.340	8.934	59.518
3	.974	6.493	66.012			
4	.825	5.499	71.511			
5	.683	4.554	76.065			
6	.613	4.088	80.153			
7	.586	3.909	84.062			
8	.494	3.294	87.355			
9	.406	2.705	90.061			
10	.311	2.072	92.133			
11	.275	1.833	93.965			
12	.265	1.764	95.730			
13	.234	1.557	97.286			
14	.222	1.483	98.770			
15	.185	1.230	100.000			

Extraction Method: Principal Component Analysis

As shown in Figure 2, the scree plot indicates a substantial decline in eigenvalues from the first to the subsequent components, followed by a progressively flatter pattern. The first component has an eigenvalue of 7.588 and explains 50.585% of the total variance in the 15 Competitive Advantage indicators, while the second component has an eigenvalue of 1.340 and accounts for an additional 8.934% of the variance. Although the second component exceeds the conventional eigenvalue threshold of 1, the scree plot indicates that the first component represents the dominant dimension, accounting for substantially more variance than the remaining components. The results therefore provide evidence of a strong dominant component underlying the Competitive Advantage indicators. On the basis of the scree test and the clear dominance of the first component—rather than the Kaiser eigenvalue-greater-than-one rule, under which two components would be retained—the first component was retained as the principal representation of Competitive Advantage for subsequent analysis, subject to the observed component loadings and the theoretical coherence of the indicators.

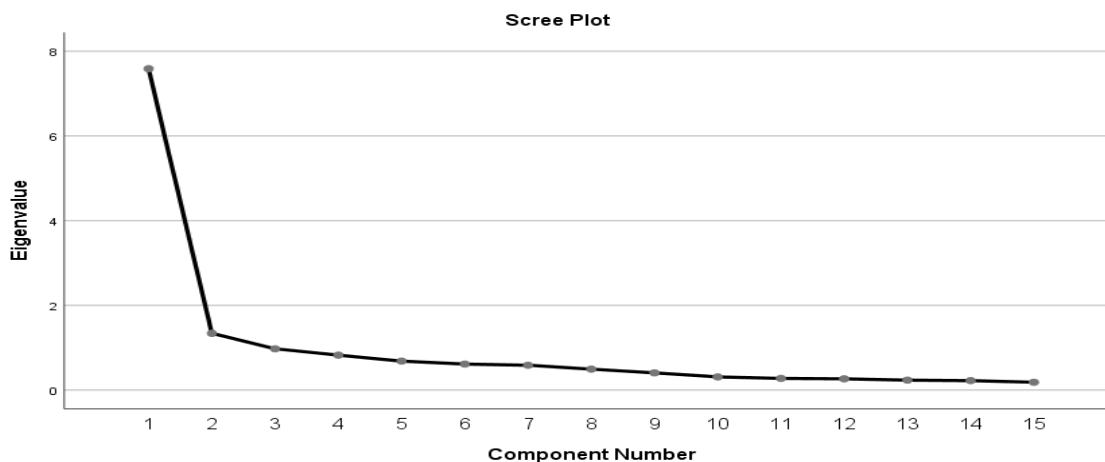


Figure 2: Scree Plot for Competitive Advantage



Table 9 shows that the 15 Competitive Advantage indicators loaded more strongly on Component 1, with loadings ranging from 0.583 to 0.855. Most indicators demonstrated substantially higher loadings on Component 1 than on Component 2, indicating that Component 1 captured the dominant aspects of Competitive Advantage, including value capture, digital innovation, differentiation, and organisational agility. However, some indicators showed notable secondary loadings on Component 2, particularly the first-mover adoption of innovative digital banking solutions (0.595) and maximisation of returns from digital transformation (0.509). Overall, the loading pattern indicates a strong dominant component underlying the Competitive Advantage indicators, supporting the retention of Component 1 as the principal representation of the construct for subsequent analysis.

Table 9: Component Matrix for Competitive Advantage

	Component	
	1	2
Our bank effectively captures value from its digital investments.	.806	-.369
The organisation has systems in place to convert digital capabilities into long-term competitive advantage.	.690	.179
Our bank maximises returns from digital transformation efforts.	.657	.509
The organisation sustains value creation through digital initiatives.	.605	.170
The bank offers digital products and services that are perceived as valuable by customers.	.804	-.229
Our organisation has developed new business models enabled by digital technologies.	.768	-.089
Digital channels have expanded the bank's revenue streams significantly.	.719	-.080
Our bank leverages digital tools to offer unique services that stand out in the market.	.855	.109
The organisation promotes a culture of innovation driven by digital initiatives.	.749	-.231
Our bank's use of digital technologies enhances product and service differentiation.	.583	-.454
The organization is often the first-mover in adopting innovative digital banking solutions.	.612	.595
Our bank quickly responds to market changes using digital capabilities.	.795	.275
The organisation adapts digital strategies in response to customer feedback and competitive trends.	.627	-.023
Our bank continuously evolves its digital services to meet changing customer demands.	.672	-.333
The organisation demonstrates agility in adjusting digital processes to respond to external shifts.	.654	.071

Extraction Method: Principal Component Analysis.

a. 2 components extracted.

Digital Sensing Capability and Competitive Advantage

Market Sensing

As illustrated in Table 10, respondents agreed that the organisation regularly monitors customer preferences to identify emerging digital needs ($M = 4.393$, $SD = 0.740$). They also agreed that the organisation frequently engages in discussions about market-driven digital opportunities ($M = 4.312$, $SD = 0.823$), and that the organisation actively tracks competitor activities to anticipate market shifts ($M = 4.257$, $SD = 0.774$). The standard deviations, all below 1.0, indicate a relatively high level of consensus among respondents and low variability in their perceptions regarding market-driven digital orientation.

Table 10: Descriptive Statistics for Market Sensing

Statements	N	Mean	Std. Dev
Our organisation regularly monitors customer preferences to identify emerging digital needs.	183	4.393	.740
The organisation actively tracks competitor activities to anticipate market shifts.	183	4.257	.774
The organisation frequently engages in discussions about market-driven digital opportunities.	183	4.312	.823
Average		4.321	0.779

Technology Sensing

According to Table 11, respondents agreed that the organisation receives regular insights into technological trends in the banking industry ($M = 4.410$, $SD = 0.826$). They also agreed that the



organisation routinely assesses the impact of new technologies on its business model ($M = 4.344$, $SD = 0.875$), and that the organisation continually scans for emerging digital technologies relevant to banking ($M = 4.273$, $SD = 0.846$). Further, the respondents agreed that the organisation invests in systems that help identify future digital innovations ($M = 4.191$, $SD = 0.921$). Overall, the average mean ($M = 4.305$, $SD = 0.867$) indicates general agreement that the organisation actively engages in technology sensing, while the standard deviation reflects moderate variability in respondents' perceptions of the organisation's practices in identifying, monitoring, and assessing emerging digital technologies.

Table 11: Descriptive Statistics for Technology Sensing

Statements	N	Mean	Std. Dev
Our organisation continually scans for emerging digital technologies relevant to banking.	183	4.273	.846
The organisation invests in systems that help identify future digital innovations.	183	4.191	.921
Our organisation routinely assesses the impact of new technologies on its business model.	183	4.344	.875
The organisation receives regular insights into technological trends in the banking industry.	183	4.410	.826
Average		4.305	0.867

Internal Sensing

As shown in Table 12, respondents agreed that the organisation conducts regular evaluations of digital capabilities and gaps ($M = 4.388$, $SD = 0.843$). They also agreed that our organisation encourages staff to suggest digital improvements to operations ($M = 4.366$, $SD = 0.681$) and that the organisation monitors internal processes to identify areas that can benefit from digitisation ($M = 4.306$, $SD = 0.773$). The respondents further agreed that the organisation has systems in place to gather internal feedback on digital readiness ($M = 4.077$, $SD = 0.929$). Overall, the average mean ($M = 4.284$, $SD = 0.807$) indicates general agreement that the organisation actively engages in internal digital sensing, while the standard deviation reflects moderate variability in respondents' perceptions regarding internal process monitoring, feedback systems, and capability evaluations.

Table 22: Descriptive Statistics for Internal Sensing

Statements	N	Mean	Std. Dev
The organisation monitors internal processes to identify areas that can benefit from digitisation.	183	4.306	.773
Our organisation encourages staff to suggest digital improvements to operations.	183	4.366	.681
The organisation has systems in place to gather internal feedback on digital readiness.	183	4.077	.929
Our organisation conducts regular evaluations of digital capabilities and gaps.	183	4.388	.843
Average		4.284	0.807

Factor Analysis for Digital Sensing Capability

The Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy is 0.908, indicating a good level of suitability for factor analysis, as values above 0.6 are considered acceptable. This suggests that the sample size and correlations among variables are sufficient for principal component analysis (PCA). Bartlett's Test of Sphericity is highly significant ($\chi^2 = 1083.302$, $df = 55$, $p < 0.001$), indicating that the correlation matrix is not an identity matrix and that significant relationships exist among the variables. These results confirm that PCA can be meaningfully applied to the dataset.

Table 33: KMO and Bartlett's Test for Digital Sensing Capability

KMO and Bartlett's Test			
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.			.908
Bartlett's Test of Sphericity	Approx. Chi-Square		1083.302
	df		55
	Sig.		.000



Table 14 shows that the first principal component for Digital Sensing Capability has an eigenvalue of 6.022 and explains 54.742% of the total variance in the 11 indicators. This indicates that the first component accounts for a substantial proportion of the variability in the indicators and represents a common underlying dimension of digital sensing capability. The remaining components have eigenvalues below 1 and were not extracted in the final solution. Therefore, only the first principal component was retained, consistent with the study's conceptualisation of digital sensing capability as a unidimensional construct. The 54.742% of variance explained by the first component provides evidence that the indicators share a substantial common dimension and supports their aggregation into a composite measure of digital sensing capability for subsequent analysis.

Table 44: Total Variance Explained for Digital Sensing Capability

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.022	54.742	54.742	6.022	54.742	54.742
2	.872	7.929	62.670			
3	.731	6.645	69.315			
4	.668	6.069	75.384			
5	.595	5.407	80.791			
6	.506	4.602	85.393			
7	.464	4.219	89.612			
8	.353	3.213	92.825			
9	.310	2.821	95.646			
10	.260	2.361	98.007			
11	.219	1.993	100.000			

Extraction Method: Principal Component Analysis

As shown in Figure 3, the scree plot supports retaining the first principal component of Digital Sensing Capability. The first component has an eigenvalue of 6.022 and explains 54.742% of the total variance, followed by a marked decline in eigenvalues for the subsequent components. The scree plot shows a clear elbow after the first component, with the curve flattening thereafter, indicating that the remaining components contribute relatively less to explaining the variance in the data. Therefore, retaining the first principal component is justified, as it captures the largest proportion of the variance and provides a parsimonious representation of the Digital Sensing Capability construct for subsequent analysis.

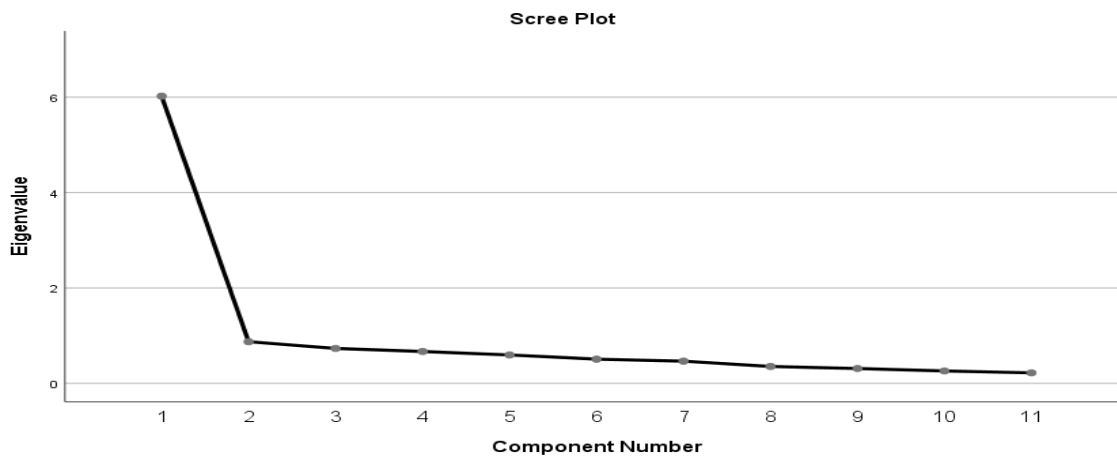


Figure 3: Scree Plot for Digital Sensing Capability



Table 15 shows that all Digital Sensing Capability indicators loaded on a single component, with factor loadings ranging from 0.648 to 0.827. The results indicate that all indicators adequately represented the underlying Digital Sensing Capability construct. The indicators captured the three dimensions of Digital Sensing Capability examined in the study: market sensing, technology sensing, and internal sensing. Market sensing was reflected through monitoring customer preferences, competitor activities, and emerging digital market opportunities; technology sensing through scanning emerging digital technologies, assessing technological trends, and evaluating their potential impact on the business; while internal sensing was reflected through monitoring internal processes, gathering employee feedback, and evaluating digital capabilities and gaps. The extraction of a single component indicates that these dimensions collectively represent a common underlying construct of Digital Sensing Capability, supporting the use of the indicators to compute a composite measure for subsequent statistical analysis.

Table 55: Component Matrix for Digital Sensing Capability

	Component 1
Our organisation regularly monitors customer preferences to identify emerging digital needs.	.827
The organisation actively tracks competitor activities to anticipate market shifts.	.728
The organisation frequently engages in discussions about market-driven digital opportunities.	.667
Our organisation continually scans for emerging digital technologies relevant to banking.	.818
The organisation invests in systems that help identify future digital innovations.	.777
Our organisation routinely assesses the impact of new technologies on its business model.	.752
The organisation receives regular insights into technological trends in the banking industry.	.699
The organisation monitors internal processes to identify areas that can benefit from digitisation.	.804
Our organisation encourages staff to suggest digital improvements to operations.	.711
The organisation has systems in place to gather internal feedback on digital readiness.	.648
Our organisation conducts regular evaluations of digital capabilities and gaps.	.681

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

Diagnostic Tests for Digital Sensing Capability and Competitive Advantage

Diagnostic tests included assessments of model fitting, the proportional odds assumption, model summary, and pseudo R-square to evaluate the adequacy, fit, and reliability of the ordinal logit regression model.

Model Fitting Test: The model fitting results indicate a significant improvement in model fit when Digital Sensing Capability is included in the ordinal logistic regression model. The intercept-only model had a -2 Log Likelihood value of 277.982, which decreased to 91.196 for the final model, indicating a substantial improvement in model fit. The likelihood ratio Chi-square was 186.786 with 1 degree of freedom and was statistically significant ($p < .001$). This indicates that the final model fits the data significantly better than the intercept-only model. The results therefore provide evidence that Digital Sensing Capability significantly contributes to explaining the ordered levels of Competitive Advantage among commercial banks in Kenya.

Proportional Odds Assumption Test: The proportional odds assumption was assessed using the Test of Parallel Lines. However, the test could not be performed because the general model failed to converge after the maximum number of step-halving iterations. SPSS therefore did not provide a valid chi-square or significance value for testing the assumption. Consequently, the proportional odds assumption could not be formally confirmed from the estimated model, and the results were interpreted with caution.

Ordinal logistic regression model: The Nagelkerke Pseudo R^2 was 0.749. This indicates that Digital Sensing Capability provides substantial information regarding the ordered levels of Competitive



Advantage among commercial banks in Kenya. The Nagelkerke Pseudo R^2 is reported as a pseudo- R^2 index with no percentage attached, since pseudo- R^2 measures in ordinal logistic regression do not have the same interpretation as R^2 in ordinary least-squares regression. The SPSS Pseudo R-Square output is reported in Table 15a.

Table 15a: Pseudo R-Square (SPSS Output)

Pseudo R-Square	
Cox and Snell	.640
Nagelkerke	.749
McFadden	.530

Link function: Logit.

Categorisation of Competitive Advantage: Table 15 presents the frequency distribution of the categorised Competitive Advantage composite score. The results show that no respondent fell within the very low category (1.00–1.80), while 6 respondents (3.3%) were classified in the low category (1.81–2.60) and 9 (4.9%) in the moderate category (2.61–3.40). The majority of respondents, 98 (53.6%), were classified in the high Competitive Advantage category (3.41–4.20), while 70 (38.3%) fell within the very high category (4.21–5.00). Overall, 91.9% of respondents were in the high or very high categories, indicating that the participating commercial banks generally reported relatively high levels of Competitive Advantage. All 183 respondents had valid observations, with no missing cases. The composite Competitive Advantage score was computed as the mean of the 15 indicators and categorised into five ordered bands of equal width (0.80 units) across the 1.00–5.00 scale, which defined the cut-points reported above.

Table 15b: Frequency Distribution and Mean-Score Ranges of Categorised Competitive Advantage

Competitive Advantage Category	Mean-Score Range	Frequency (N)	Percentage (%)
1.00	1.00–1.80	0	0.0
2.00	1.81–2.60	6	3.3
3.00	2.61–3.40	9	4.9
4.00	3.41–4.20	98	53.6
5.00	4.21–5.00	70	38.3
Total	1.00–5.00	183	100.0

Parameter Estimates: Table 16 presents the parameter estimates from the ordinal logistic regression model. The three threshold estimates for Competitive Advantage were statistically significant: CA = 2.00 ($\beta = 20.394$, SE = 2.805, Wald = 52.853, $p < .001$), CA = 3.00 ($\beta = 25.512$, SE = 3.283, Wald = 60.402, $p < .001$), and CA = 4.00 ($\beta = 31.374$, SE = 3.689, Wald = 72.334, $p < .001$). These thresholds represent the estimated cut-points between the ordered Competitive Advantage categories and are not interpreted as substantive predictor effects. Digital Sensing Capability (DSC) had a positive and statistically significant coefficient ($\beta = 6.932$, SE = 0.817, Wald = 71.988, $p < .001$, 95% CI [5.331, 8.533]). The corresponding odds ratio, $\text{Exp}(\beta)$, was approximately 1,025, indicating a very large estimated increase in the odds of being in a higher Competitive Advantage category for a one-unit increase in DSC. However, the exceptionally large coefficient and odds ratio warrant caution because they may reflect quasi-complete separation in the data, which can produce unstable maximum-likelihood estimates and inflated statistical significance. Therefore, the observed positive association should not be interpreted as a stable population-level effect without further assessment of separation. The cross-tabulation of the categorised Competitive Advantage outcome against DSC should be examined, and the model should be re-estimated using an appropriate penalised-likelihood approach. Subject to this diagnostic and re-estimation, the results provide evidence of a positive association between Digital Sensing Capability and higher levels of Competitive Advantage.



Table 16: Parameter Estimates

							95% Confidence Interval	
		Estimate	Std. Error	Wald	df	Sig.	Lower Bound	Upper Bound
Threshold	[CA_1 = 2.00]	20.394	2.805	52.853	1	.000	14.896	25.893
	[CA_1 = 3.00]	25.512	3.283	60.402	1	.000	19.079	31.946
	[CA_1 = 4.00]	31.374	3.689	72.334	1	.000	24.144	38.604
Location	DSC	6.932	.817	71.988	1	.000	5.331	8.533

Link function: Logit.

Discussion of the Results

The study found that Digital Sensing Capability had a positive and statistically significant effect on the Competitive Advantage of commercial banks in Kenya. The finding indicates that strengthening market sensing, technology sensing, and internal sensing enables banks to enhance their ability to identify emerging customer needs, anticipate technological developments, and recognise internal opportunities for digital improvement, thereby strengthening their competitive positioning. Empirically, the positive coefficient for Digital Sensing Capability ($\beta = 6.932$, $p < .001$) demonstrates a strong positive relationship with higher levels of Competitive Advantage. The Nagelkerke Pseudo R^2 of 0.749 further indicates that the ordinal logistic regression model had substantial explanatory strength in accounting for variations in the ordered levels of Competitive Advantage. The finding therefore provides strong empirical evidence that Digital Sensing Capability is significantly associated with Competitive Advantage among commercial banks in Kenya.

The findings provide strong support for Dynamic Capabilities Theory, particularly its sensing dimension. The theory posits that firms operating in dynamic environments can strengthen their competitive position by developing capabilities to continuously identify changes, opportunities, and threats in their external and internal environments. These findings are also consistent with Sudrajat et al. (2019), who found that sensing capability positively and significantly influenced innovative logistics services, which subsequently enhanced financial outcomes. Similarly, Wong and Ngai (2025) established that analytics capability and sensing capability significantly influenced operations performance, while Ojo (2025) found that sensing capabilities contributed significantly to the growth performance of MSMEs in Nigeria. The findings are also supported by Kenyan evidence. Ng'ang'a et al. (2024) established a significant relationship between sensing capabilities and organisational performance among supermarkets, while Bett and Anene (2023) found that sensing capabilities significantly influenced the performance of small and medium agrifood enterprises in Nairobi County. Indeje and Mutua (2024) further reported a significant influence of sensing capabilities on competitive advantage in Kenya's telecommunication industry.

The consistency of these findings is particularly relevant to commercial banks in Kenya because the country's banking sector operates within a highly dynamic digital financial ecosystem characterised by widespread mobile money, digital payment platforms, fintech integration, and evolving regulatory requirements. Consequently, Kenyan banks must continuously sense changes in customer digital preferences, technological developments, competitor initiatives, and regulatory expectations to adapt their digital services and sustain Competitive Advantage. Thus, the positive effect identified in this study reflects the specific need for Kenyan commercial banks to integrate internal sensing mechanisms with rapidly evolving external digital financial infrastructures and institutional conditions.

A methodological consideration in interpreting these findings is that the study collected data anonymously and did not record the specific commercial bank associated with each respondent. Consequently, it was not possible to account for potential within-bank clustering or estimate the intraclass correlation. Although respondents were drawn from 37 commercial banks, the analysis was conducted at the individual respondent level without modelling the hierarchical structure of the data.



Therefore, the reported standard errors, p-values, and confidence intervals may be optimistic if meaningful within-bank clustering was present. The findings should consequently be interpreted as evidence of a statistically significant association between Digital Sensing Capability and Competitive Advantage as perceived by bank managers, rather than as a direct bank-level causal estimate. This limitation should be considered when interpreting the statistical significance and generalising the findings to individual commercial banks. For future studies, anonymity could be maintained by assigning a non-identifying coded institution identifier to each respondent, thereby enabling the assessment of within-bank clustering and the use of multilevel or cluster-robust analytical approaches.

Conclusion

The study found that Digital Sensing Capability was positively and statistically significantly associated with Competitive Advantage among commercial banks in Kenya. The study concludes that Digital Sensing Capability is not merely a technical or operational function but is an important strategic capability associated with Competitive Advantage in the banking sector. The findings suggest that banks with stronger capabilities for market sensing, technology sensing, and internal sensing tend to report higher levels of Competitive Advantage. The study recommends that bank executives strengthen Digital Sensing Capability by institutionalising mechanisms for market, technology, and internal sensing. Management should continuously monitor customer preferences, emerging digital technologies, competitor activities, and internal digital capabilities to support timely strategic decision-making and strengthen the bank's capacity to respond to competitive conditions. Banks should establish cross-functional teams involving ICT, strategy, marketing, operations, and risk functions to interpret digital intelligence and inform strategic responses. Regulators should strengthen data governance and cybersecurity frameworks and develop clear open banking and API standards to support secure data sharing and digital innovation while protecting customer information. These measures may support the development of Digital Sensing Capability and Competitive Advantage within the banking sector.

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