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AI Predictive and Analytics on Strategic Decision-Making: A Case of Safaricom Kenya Limited

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ABSTRACT

Telecom firms collect vast amounts of data, yet heavy AI investment often fails to improve the strategic decisions managers actually make. This study examined two AI capabilities, predictive analytics and analytical sophistication, and their effect on strategic decision-making at Safaricom Kenya Limited. It pursued two objectives: to examine the effect of AI predictive analytics capability on strategic decision-making, and to assess the effect of AI analytical sophistication on strategic decision-making. The work draws on the Resource-Based View, Dynamic Capabilities Theory, Decision Theory, and the Technology-Organization-Environment framework. Using a descriptive survey design, a sample of 124 senior managers was drawn from a target population of 180 by the Yamane formula and stratified random sampling; 120 valid questionnaires were returned (96.8%). Data were analysed in SPSS using Pearson correlation and simple and multiple linear regression. Both capabilities correlated positively and significantly with strategic decision-making: predictive analytics ($r = 0.833$) and analytical sophistication ($r = 0.546$), both $p < 0.001$. On its own, predictive analytics explained 69.3% of the variation and analytical sophistication 29.8%. In the full four-capability model ($R^2 = 0.906$), predictive analytics remained a significant unique driver ($\beta = 0.531$, $p < 0.001$) while analytical sophistication did not ($\beta = 0.118$, $p = 0.142$). The study recommends that Safaricom prioritise predictive analytics in its AI investment and treat analytical sophistication as a supporting capability that feeds, rather than replaces, forward-looking tools.

Keywords: Artificial Intelligence; predictive analytics; analytical sophistication; strategic decision-making; Safaricom

1. Introduction

Business conditions change quickly and are hard to predict, and that pressure has pushed managers to rethink how they make strategic decisions. For years those decisions rested on the intuition and experience of senior executives, but that approach struggles as technology, customers, and competition shift faster (Theodorakopoulos et al., 2025; Brem, 2024). AI offers a different footing because it can process far more data, faster and with fewer errors, than people can alone. Adoption has grown quickly, with 88% of organisations now using AI in at least one business function (McKinsey & Company, 2025).

Kenya's telecommunications industry is among the most competitive in Africa. Safaricom Kenya Limited leads the market, serving 37.1 million one-month active customers and earning service revenue of KShs 364.3 billion in its 2025 financial year (Safaricom, 2025). For a firm that size, the problem is no longer collecting data but using it well. This article looks at two AI capabilities that bear directly on that problem: predictive analytics, which forecasts risks and opportunities, and analytical sophistication, which processes large, varied data to support decisions.

The study addressed two objectives at Safaricom Kenya Limited:

1. To examine the effect of AI predictive analytics capability on strategic decision-making.
2. To assess the effect of AI analytical sophistication on strategic decision-making.

2. Literature Review

The study rests on four theories. The Resource-Based View (Barney, 1991) frames AI capabilities as potentially valuable, rare, hard-to-imitate resources. Dynamic Capabilities Theory (Teece, Pisano & Shuen, 1997) explains how firms turn such resources into agile decisions. Decision Theory (Von Neumann & Morgenstern, 1944) describes the decision outcomes through which value is realised, noting that human rationality is bounded by bias (Simon, 1955) that data-driven inputs can offset. The Technology-Organization-Environment framework (Tornatzky & Fleischer, 1990) captures the conditions that enable or constrain adoption.

On predictive analytics, Accenture (2022) and Wamba et al. (2020) link predictive AI to better forecasting and more evidence-based decisions, and locally Muriuki (2022) found predictive AI supported forecasting at Safaricom, though it was not always carried into senior decisions. On analytical sophistication, McKinsey & Company (2021) and PwC Africa (2022) connect advanced analytics to decision quality and network performance, while Otieno (2023) found AI analytics improved decision quality at Safaricom but identified a partial utilisation gap tied to how managers interpret the outputs. Two gaps follow: studies rarely separate specific AI capabilities, and firm-level, statistically grounded African evidence is scarce. This article addresses both for predictive analytics and analytical sophistication.

3. Methodology

The study used a quantitative, descriptive survey design. The target population was 180 senior staff at Safaricom's Nairobi headquarters across the Operations, Marketing, IT, and Finance functions. Using the Yamane (1967) formula at a 5% margin of error, a sample of 124 was drawn by stratified random sampling; 120 questionnaires were completed and returned, a response rate of 96.8%. Predictive analytics and analytical sophistication were measured on five-point Likert items, as was strategic decision-making (decision speed, quality, risk mitigation, and alignment with goals). Data were analysed in SPSS using Pearson correlation and simple and multiple linear regression at the 5% significance level. Both constructs were reliable, with Cronbach's Alpha of 0.854 for predictive analytics and 0.710 for analytical sophistication, against an overall index of 0.782.

4. Results

4.1 AI Predictive Analytics

Respondents agreed that predictive analytics supported their decisions. Pearson correlation showed a strong, significant positive relationship with strategic decision-making ($r = 0.833$, $p < 0.001$). Simple regression indicated that predictive analytics alone explained 69.3% of the variation in strategic decision-making ($R^2 = 0.693$), $F(1,118) = 266.690$, $p < 0.001$, with $\beta = 0.833$ and $B = 0.562$ ($t = 16.331$, $p < 0.001$). The null hypothesis of no significant effect was rejected.

4.2 AI Analytical Sophistication

Analytical sophistication also mattered, though less strongly. Correlation showed a moderate, significant positive relationship ($r = 0.546$, $p < 0.001$). Simple regression indicated that it explained 29.8% of the variation ($R^2 = 0.298$), $F(1,118) = 50.132$, $p < 0.001$, with $\beta = 0.546$ and $B = 0.653$ ($t = 7.080$, $p < 0.001$). The null hypothesis was rejected. Table 1 summarises both results.

AI Capability	**Pearson r**	**Sig. (2-tailed)**	**Simple-regression R^2**
AI Predictive Analytics	0.833	0.000	0.693
AI Analytical Sophistication	0.546	0.000	0.298

Table 1: Correlation and Individual Explanatory Power (N = 120). Source: Research Data (2026)

4.3 Multiple Regression

Both capabilities were entered into the full four-capability model, which was strong and significant ($R^2 = 0.906$, $F(4,115) = 276.403$, $p < 0.001$). Once the other capabilities were controlled, predictive analytics stayed a significant unique driver ($\beta = 0.531$, $p < 0.001$), but analytical sophistication did not ($\beta = 0.118$, $p = 0.142$). Table 2 reports the two relevant coefficients.

Predictor	B	Std. Error	Beta	t	Sig.
(Constant)	-0.465	0.166		-2.802	0.006
AI Predictive Analytics	0.358	0.049	0.531	7.310	0.000
AI Analytical Sophistication	0.141	0.095	0.118	1.480	0.142

Table 2: Multiple Regression Coefficients for Predictive Analytics and Analytical Sophistication. The model also controlled for pattern recognition and prescriptive capability; full model $R^2 = 0.906$, $F(4,115) = 276.403$, $p < 0.001$. Source: Research Data (2026)

5. Discussion

The results point to a clear difference between the two capabilities. On its own, each is significant, but predictive analytics does far more work: it explains 69.3% of the variation against 29.8% for analytical sophistication. The gap widens in the combined model, where predictive analytics remains a strong unique driver while analytical sophistication loses significance. The most likely reason is shared variance. Analytical sophistication and predictive analytics draw on the same underlying data work, so once the forward-looking capability is in the model, analytics adds little on its own. This matches Decision Theory, which stresses reducing uncertainty before acting, and it echoes Otieno's (2023) utilisation gap: analytics clearly informs decisions, but often by feeding predictive tools rather than driving decisions directly.

6. Conclusion and Recommendations

Both predictive analytics and analytical sophistication are positively linked to strategic decision-making at Safaricom, but predictive analytics is the stronger and more durable driver. Analytical sophistication matters mainly as a supporting capability. The study recommends two things. First, Safaricom should prioritise predictive analytics in its AI investment, since it delivers the most decision value. Second, it should position analytical sophistication as the data backbone that feeds predictive tools, and invest in managerial skills so that analytical outputs are read and used rather than left as reports. Future work could test, through mediation analysis, whether analytical sophistication works mainly through predictive analytics, as these results suggest.

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