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ORGANIZATIONAL AGILITY ON PERFORMANCE OF MANUFACTURING SMALL AND MEDIUM SIZED ENTERPRISES IN NAIROBI, KENYA

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ABSTRACT
This paper empirically examines the relationship between organizational agility and the performance of manufacturing small and medium enterprises (SMEs) in Nairobi, Kenya. The study focused on four key dimensions of agility: sensing agility, decision-making agility, resource fluidity, and cultural contours. Using an explanatory research design, the study targeted 987 registered manufacturing SMEs and employed a multi-stage sampling approach stratified, proportionate, and simple random sampling to select a sample of 284 SME owners and managers, determined through Yamane's formula. Primary data were collected using structured, close-ended questionnaires and analyzed through descriptive and inferential statistics. The findings reveal that sensing agility, decision-making agility, resource fluidity, and cultural contours each exert a positive and statistically significant effect on SME performance. This suggests that agility enables firms to sense environmental shifts, make swift and informed decisions, flexibly reallocate resources, and foster cultures that support adaptability and resilience. The study concludes that organizational agility is a critical determinant of SME performance in dynamic markets. It recommends that manufacturing SMEs institutionalize agile practices by investing in real-time market sensing mechanisms, decentralizing decision-making structures, ensuring flexible resource allocation, and cultivating adaptive cultural values to sustain competitiveness and performance.
KEY WORDS: *Organizational Agility, Sensing Agility, Decision-Making Agility, Resource Fluidity, Cultural Contours, SME Performance, Manufacturing SMEs, Kenya,*

1. INTRODUCTION

Organizational agility has risen to the foreground of management practice as manufacturing small and medium enterprises (SMEs) navigate a confluence of shocks—pandemic aftershocks, supply-chain volatility, inflationary pressures, and rapid digitization—against a backdrop of intensifying local and global competition. In Kenya, manufacturing remains a strategic pillar under the Bottom-Up Economic Transformation Agenda, yet its contribution to gross domestic product (GDP) has hovered in the single digits—about 7.6% of GDP in 2023—underscoring the need for capability upgrades that can translate turbulence into performance (growth, profitability, quality, and customer responsiveness). Within the Kenyan production landscape, Nairobi City County is the industrial hub: it generated about 27.5% of national gross value added between 2019 and 2023 and led all counties in manufacturing activity over 2018–2022, reflecting the concentration of plants, skilled labor, and enabling services in the capital. This concentration makes Nairobi an ideal locus for studying how organizational agility—and specifically sensing agility, decision-making agility, resource fluidity, and cultural contours—relates to SME performance under dynamic market conditions. At the same time, operating constraints remain salient: the World Bank Enterprise Survey (2018) reported that a high share of Kenyan firms experienced power interruptions and associated losses, while finance frictions persist, with an estimated MSME credit gap of roughly USD 19.3 billion. These boundary conditions heighten the strategic premium on agile capabilities that help SMEs anticipate shifts, decide quickly and well, reallocate scarce resources, and sustain cultures that align people and processes with change (KNBS, 2024; KNBS, 2023; World Bank, 2018; FSD Kenya, 2024).

Globally, empirical evidence linking agility to organizational outcomes is increasingly consistent. A recent systematic review of 249 empirical studies (1998–2024) concluded that agility in its various forms is a strong, reliable predictor of firm performance across sectors and contexts. Notably, the review highlights gaps highly relevant to Nairobi's SME setting: a continued reliance on cross-sectional designs, uneven measurement across agility subdomains, and under-emphasis on board-level/leadership drivers of agility—limitations that call for context-specific research on how sensing, decision-making, resource fluidity, and culture jointly shape outcomes in emerging economies (Nguyen et al., 2024).

Within this broader canvas, sensing agility—an organization's capability to scan, interpret, and anticipate shifts in markets, technologies, regulations, and supply conditions—anchors the agility-to-performance pathway in turbulent environments. For manufacturing SMEs in Nairobi, sensing spans structured activities (market intelligence, customer co-creation, supplier listening) and unstructured signals (informal distributor feedback, policy cues). Empirical work post-2020 strengthens the performance link: studies of MSMEs and technology-intensive firms show that stronger sensing capabilities, often in tandem with analytics and data capabilities, are associated with higher operational and innovation performance. This reflects improved opportunity recognition, faster risk detection, and earlier pivoting to cost-effective inputs or product-market niches—critical for SMEs exposed to exchange-rate swings and input-cost volatility in Kenya (Aneiro et al., 2023; Umulkher & Gichinga, 2024). Moreover, Nairobi's heavy industrial clustering implies rich, real-time information flows—competitor actions, demand micro-shifts, or logistics bottlenecks—that SMEs can harness if their sensing routines are systematic and embedded in leadership attention cycles (Nguyen et al., 2024; World Bank, 2018).

Decision-making agility—the capacity to make timely, high-quality strategic and operational decisions under uncertainty—translates sensed signals into coordinated action. Contrary to the canonical speed-accuracy trade-off, recent research shows teams can achieve both fast and high-quality decisions through behavioral integration—dense, multi-directional information exchange that builds shared understanding and procedural justice in top-team processes. In effect, behavioral integration streamlines the "black box" from signal to choice, dampening politics and accelerating consensus. For Nairobi manufacturers, where production scheduling, inventory hedging, and sourcing trade-offs must be made under power instability and supplier variability, decision processes that combine speed with rigor underpin cycle-time reliability, quality adherence, and customer fill rates—hard performance metrics central to SME survival. The implication is direct: investments in decision forums (e.g., daily operations huddles with clear escalation rules), data visibility (e.g., end-to-end order dashboards), and leadership rituals (e.g., premortems/after-action reviews) are performance levers, not merely governance hygiene (Shepherd et al., 2023).

Resource fluidity—the ability to redeploy people, capital, capacity, and attention at minimal friction—forms the executional backbone of agility. Recent studies that decompose strategic agility into its constituent capabilities (strategic sensitivity/sensing, leadership unity/deciding, and resource fluidity/reconfiguring) find that environmental turbulence generally raises the returns to agility and that firm age can dampen agility components, including resource fluidity. For Nairobi SMEs, resource fluidity has concrete expressions: cross-training operators to move across workstations; modularizing production lines to switch SKUs; re-sequencing capex portfolios as credit conditions change; and reallocating working capital across sales channels as demand migrates (e.g., from institutional to retail). The large MSME finance gap and episodic liquidity pressures accentuate the need for operating models that can flex resources rapidly without excessive switching costs; where credit is scarce or expensive, internal resource mobility substitutes for external finance in stabilizing throughput and service levels (de Diego Ruiz et al., 2024; FSD Kenya, 2024).

Cultural contours—norms, values, and shared assumptions that shape attention, collaboration, and learning—amplify or blunt the other agility components. Evidence from emerging-economy SMEs shows that cultural traits emphasizing adaptability, learning, and involvement correlate positively with business performance and often mediate the effects of strategic postures on outcomes. For manufacturing SMEs, adaptive cultures support problem-solving on the shop floor, continuous improvement, and psychological safety for raising quality issues early—behaviors tightly bound to defect rates, on-time delivery, and customer satisfaction. In Nairobi, where workforces are diverse and labor markets are competitive for skilled technicians, cultural attributes that promote inclusion, clarity of purpose, and accountability help reduce turnover and accelerate skill diffusion, further reinforcing resource fluidity and decision speed. While culture is context-laden, empirical results from African and comparable contexts suggest that "agility-consistent" cultural profiles (e.g., learning orientation, collaboration, disciplined execution) materially enhance SME performance (Zehira & Alkider, 2022; Nguyen et al., 2024).

The Kenyan context sharpens these relationships. First, infrastructure and input-market frictions magnify the value of early sensing and fast, integrative decisions: power unreliability can disrupt batch yields and delivery schedules; foreign-exchange volatility shifts landed input costs; and regulatory adjustments alter compliance costs. Firms that sense early and decide quickly can hedge inputs opportunistically, reschedule preventive maintenance around anticipated outages, and re-price orders with minimal margin erosion. Second, finance constraints make resource fluidity a performance differentiator: when external funding is rationed, SME leaders must "manufacture" liquidity through internal reallocations (e.g., from lower-velocity SKUs to fast-moving ones) and capital productivity (e.g., higher overall equipment effectiveness). Third, Nairobi's dense industrial and service ecosystems equip firms that cultivate learning cultures to exploit network spillovers—supplier development programs, OEM clinics, or association trainings—converting community knowledge into plant-level performance routines (World Bank, 2018; FSD Kenya, 2024; KNBS, 2023).

These agility-performance links also intersect with Kenya's digitalization trajectory. While OECD analyses emphasize how digital tools strengthen SME agility via data visibility and coordination, Nairobi manufacturers face uneven adoption and affordability gaps. Firms that embed lightweight digital enablers—mobile-based order capture, basic manufacturing execution system (MES) features, or simple analytics—enhance sensing (demand signals), decision speed (exception alerts), and resource fluidity (dynamic line balancing), often at modest cost. However, digital investments must be complemented by team behaviors (behavioral integration) and cultural norms (learning, transparency) to yield performance gains; technology alone rarely overcomes weak decision routines or rigid resource allocations (OECD, 2021; Shepherd et al., 2023).

Methodologically, the post-2018 literature counters three common concerns relevant to this study's design in Nairobi. First, construct clarity has improved: many studies now disaggregate "strategic agility" into sensing, deciding, and resource fluidity—allowing clearer inference on which component drives which performance dimension. Second, scholars increasingly model environmental turbulence and firm characteristics (size, age, internationalization) as contingencies, reducing omitted-variable bias when estimating agility effects. Third, while cross-sectional PLS-SEM designs remain frequent, a growing body of mixed-methods and longitudinal work has begun to capture dynamic capability formation and use under real turbulence—an arc that Nairobi SMEs are living daily (Nguyen et al., 2024; de Diego Ruiz et al., 2024).

In practical terms, the Nairobi SME performance equation can be read as a capability stack. Sensing agility ensures that weak signals about demand, costs, and regulation reach leadership before they become lagging indicators. Decision-making agility converts those signals into timely, high-quality choices by orchestrating multi-functional knowledge and minimizing political drag. Resource fluidity operationalizes choices by moving people, machines, and money where marginal returns are highest. Cultural contours provide the ambient conditions that keep the other three capabilities "switched on": curiosity for sensing, candor and trust for decision speed and quality, and shared purpose and discipline for resource redeployment. When this stack is coherent, SMEs improve throughput, quality, cost, and responsiveness simultaneously—outcomes observable in Nairobi's best-performing factories even under power and finance constraints (World Bank, 2018; KNBS, 2023; FSD Kenya, 2024; Shepherd et al., 2023).

Finally, Nairobi's policy and ecosystem trends create a fertile testbed. County-national programs targeting MSME productivity, associations like the Kenya Association of Manufacturers, and donor-backed supplier development efforts collectively expand access to technical assistance, standards, and markets. For research and practice, this implies rich variation in agility investments and exposure to turbulence across sub-sectors (food and beverages, metal fabrication, chemicals, textiles), enabling comparative analyses of how each agility component maps to specific performance metrics (e.g., OEE, right-first-time, service level). In sum, the confluence of structural constraints, concentrated industrial activity, and evolving support systems in Nairobi elevates organizational agility from abstract theory to a practical operating system for SME performance. The present study, therefore, situates sensing agility, decision-making agility, resource fluidity, and cultural contours at the center of the performance conversation, building on the strongest recent empirical signals while attending to the contextual realities of Kenya's manufacturing heartland (KNBS, 2024; KNBS, 2023; Nguyen et al., 2024).

The document is organized as follows: Section 2 examines the empirical literature regarding the three primary relationships under scrutiny: financial development and carbon emissions; renewable energy usage and carbon emissions; institutional quality and carbon emissions. This study's contribution to these three research domains is examined. Section 3 delineates the dataset and methodology utilized, elucidating the justification for concentrating on Sub-Saharan Africa and the measurement of essential factors. Section 4 delineates the study's conclusions using diverse analytical frameworks, whilst Section 5 examines the policy implications inferred from the results.

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

In 2023, Wong, He, Sorooshian, and Zhou examined whether analytics and sensing capabilities jointly improve micro, small, and medium enterprises' operational outcomes. Drawing on the dynamic capabilities view, they surveyed 149 MSMEs and applied structural equation modeling (SEM) to test direct and moderated effects. The study found that sensing capability—defined as systematically scanning and interpreting market/technological cues—significantly enhanced operational performance, and that a data-driven culture strengthened this relationship, underscoring how information quality and usage norms convert scanning into performance gains.

In 2023, Rahman and Islam focused on e-commerce firms to assess whether market sensing, as part of firms' digital transformation, contributes to performance. Using a survey design and PLS-SEM, they reported that robust sensing routines (continuous scanning, rapid insight generation) are positively associated with firm performance, with digital transformation readiness amplifying effects—suggesting that technology foundations help organizations translate early signals into profitable action.

In 2024, de Diego Ruiz, Almodóvar, and Birkinshaw disentangled antecedents of the three pillars of strategic agility—strategic sensitivity (a sensing analogue), leadership unity, and resource fluidity—across 220 Spanish service firms. Using PLS-SEM, they showed environmental turbulence positively shapes strategic sensitivity, implying that noisier contexts sharpen sensing routines that later channel into performance through the broader agility architecture.

In 2024, Omondi and Baraka investigated transport SMEs in Kenya, asking whether market-sensing capability—via environmental scanning and customer/competitor monitoring—improves service reliability and logistics outcomes. A descriptive-correlational survey showed significant positive links between sensing and performance, mediated by flexibility and risk mitigation, illustrating sensing's value for small firms operating in volatile county markets.

In 2021, Sholeh and Darmawan studied 330 Indonesian retail-fashion SMEs to test whether customer- and competitor-sensing capabilities influence business performance via specialized marketing capabilities. Using PLS-SEM, they found that both sensing forms directly improved performance and indirectly did so through marketing capabilities, highlighting how sensing converts into outcomes when paired with commercialization routines.

In 2024, Neiroukh, Emeagwali, and Aljuhmani examined whether AI capability enhances organizational performance by improving decision-making speed and quality. Using a cross-industry survey (N≈230) and PLS-SEM, they showed AI capability significantly and positively affects decision speed and decision quality, which in turn boost performance—evidence that "fast-and-right" decision processes are a proximate mechanism through which digital investments create value.

In 2023, Shepherd et al. (European Management Review) addressed a classic trade-off—speed versus quality in strategic decisions—by combining mixed-method field evidence with theory on behavioral integration in top teams. Their results showed that behavioral integration (information sharing, joint decision making) need not slow teams; rather, it fosters *both* speed and quality, yielding superior performance—especially when information richness and shared cognition are high.

In 2024, Grewal and colleagues investigated the relationship between decision speed and performance across environments, using multi-informant survey data from 117 UK firms. They found that environmental munificence conditions whether faster decisions pay off, revising the "faster is always better" view and indicating that speed's performance effect depends on contextual resources and information availability.

In 2024, Golan et al. (Industrial Management & Data Systems) synthesized meta-analytic evidence on knowledge technologies and decision contexts, concluding that information quality enhances decision quality and perceived task

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performance; they offered an assessment model practitioners can use to audit dashboards and analytics for decision-support effectiveness—a foundation for decision-making agility.

In 2022, Junfeng, Zesheng, and RuQiang studied customer agility in the Chinese market using PLS-SEM and found that customer-sensing and responding capabilities—proximate decision inputs and outputs—reinforce brand image and market success. The implication is that decision-making agility is energized when sensing and responding are tightly coupled by shared schemas.

In 2022–2024, supply-chain studies deepened the link between data, decision agility, and performance. Large-scale surveys using PLS-SEM and, in some cases, hybrid PLS-SEM/ANN designs showed that data network effects and AI-driven risk management increase supply-chain agility and resilience, which mediate the effect of digital transformation on performance—pointing to decision speed/quality as routes from technology to results under uncertainty.

In 2024, de Diego Ruiz et al. also illuminated resource fluidity—the rapid reallocation of budgets, assets, and talent—as an agility pillar. Their PLS-SEM results indicated that environmental turbulence and internationalization foster resource fluidity capabilities, setting the stage for faster reconfiguration and sustained performance advantages in dynamic service markets.

In 2022 and 2023, corporate strategy research clarified the economics of resource redeployment, a micro-foundation of resource fluidity. Feldman and Sakhartov (Organization Science) formalized conditions under which managers should redeploy versus divest; Feldman, McGrath, and Puig (Strategy Science) showed how “new best use” logic and organizational “pipes and prisms” shape the feasibility and value of redeployment. Together, these studies argue that when redeployment costs are low and decision rights are well-aligned, firms can capture performance gains by fluidly moving resources to higher-value uses.

In 2025 (reviewing 2020–2024 evidence), Busolo’s systematic review synthesized strategic agility drivers of performance, reporting that environmental sensing and resource fluidity consistently associate with improved operational and competitive outcomes. Although not a single empirical test, the paper aggregates recent studies to show how agility subdimensions co-produce performance in volatile markets.

In 2022–2024, international business research connected resource fluidity to business model innovation. Mixed-method and conceptual works argued that strategic sensitivity, leadership unity, and resource fluidity enable the ideation and implementation stages of business model renewal, which then elevate performance—highlighting fluidity’s role as the “reconfiguration engine” in the agility triad.

In 2023–2024, additional studies in emerging markets linked resource orchestration to performance, finding that technological opportunism and digitalization improve outcomes *through* resource structuring/redeployment and internationalization, respectively—mechanisms consistent with resource fluidity converting latent options into realized gains.

In 2021, Liu, Tsui, and Kianto conducted a meta-analysis of “knowledge-friendly” organizational culture (trust, knowledge sharing, learning orientation) and performance. Aggregating 40+ effect sizes across countries and industries, they found a robust positive association with both financial and non-financial performance, indicating that cultural contours enabling knowledge flows underpin superior results across contexts.

In 2024, Abubakari and Agyeman analyzed 382 African SMEs using SmartPLS 4 to model the culture–innovation–performance chain. They found that collaborative, open, risk-tolerant cultures significantly stimulate product, process, marketing, and organizational innovation; product innovation was the strongest performance driver. Interestingly, the direct culture–performance path was weak/negative, implying culture acts primarily through innovation capabilities—a reminder that cultural contours often exert *indirect* effects on results.

Drawing from the theoretical and empirical analyses, we formulated the following hypotheses:

H1. *Sensing agility has a significant effect on Performance*

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H2. *Decision making has a significant effect on Performance*
H3. *Resource fluidity has a significant effect on Performance*
H4. *Cultural contours has a significant effect on Performance*

3. SAMPLE AND DATA

A population is the total of all the individuals or items that have certain characteristics that are of interest to a researcher. Sekaran and Bougie (2019) describe target population as a complete set of individual case objects with some common characteristics to which researchers want to generalize the result of the study. The target population for the study was manufacturing SMEs in Nairobi County that employ 5- 99 permanent employees. There are 987 registered manufacturing SMEs of which 341 are small employing 11-49 permanent employees and 646 are medium employing 50- 99 permanent employees (Nairobi City County, 2023).

Table 1: Target Population

ENTERPRISES	NUMBER
Small Enterprises	341
Medium Enterprises	646
TOTAL	**987**

Source: *Business Register, Nairobi City County, 2023*

3.1 Sampling Design and Procedures

Sampling technique involves the method of choosing a representative sample to determine the criteria used to select appropriate respondents from the target population (Adams et al., 2007). Saunders et al. (2014) describe sampling as a method for selecting a subset from the larger population. The sampling procedure must guarantee that a representative sample of the target population is selected (Cooper & Schindler, 2014). The sample frame for obtaining the population and sample for the study was derived from the licensing records of Nairobi County. The selection of the sample occurred from three specified industrial clusters determined by their geographical location. Cluster one consisted of manufacturing SMEs located in the Industrial area, cluster two included manufacturing SMEs situated in the Ruaraka/Baba Ndogo Industrial area, while cluster three encompassed those SMEs found in the Kariobangi Industrial cluster. Sampling was conducted with careful consideration to ensure that both small and medium enterprises are well represented, reflecting the appropriate ratio of the target population of these enterprises.

During the second stage of sampling, a stratified random sampling method was employed to choose SMEs from the three clusters. Stratification is essential due to the diversity present among manufacturing SMEs regarding their size and the various activities they engage in. This study examined stratification according to the size of the enterprises, categorizing them as either small or medium enterprises. Enterprises were systematically chosen from the strata to ensure the elimination of bias. The formula for sample size calculation proposed by Yamane (1967) was utilized to determine a sample size of 284 SMEs as outlined below;

$$\boldsymbol{n = \frac{N}{1 + N(e)^2}}$$

Where:

n = Sample size

N = Population size

e = the error of Sampling

Hence

$$\frac{987}{1 + 987(0.05)2}$$

$= \mathbf{284}$

The sample of 284 is distributed as indicated in Table 2, whereby the sample distribution was based on the percentage numerical strength of each stratum.

Table 2: Sample Size

Enterprise	Population (N)	Sample Size (n)	% n/N*100
Small	341	98	28.7
Medium	646	186	28.7
Total	**987**	**284**	

Measurement of variables

Table 3: Measurement of variables

Category	Variable	Abbreviation	Measurement Items (5-Point Likert Scale)
Dependent Variable	SME Performance	SP	Increased customer satisfaction, Increased market share, Innovativeness vs competitors, Increased profits, Operational efficiency
Independent Variable	Sensing Agility	SA	Identification of market trends, Monitoring customer feedback, Real-time adaptation, Prompt response to opportunities, Use of data analytics
	Decision-Making Agility	DMA	Flexible decision-making, Empowerment at all levels, Collaborative decisions, Regular review of criteria, Swift strategic decisions
	Resource Fluidity	RF	Resource reallocation, Diverse skillsets, Adaptable infrastructure, Redirecting finances, Resource performance evaluation
	Cultural Contours	CC	Open communication, Learning from failure, Culture of agility, Challenging status quo, Cultural alignment with agility

3.3 Model specification

Hierarchical regression analysis aims to assess the predictive power of a set of factors on a certain dependent variable, to improve the accuracy of the estimation (Kumar, 2019). The hierarchical regression model used in this study is displayed below:

$Y = \beta_0 + C + \varepsilon$ ……………………………………………………………….. (1)

$Y = \beta_0 + C + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 x_4 + \varepsilon$……………..…………………… (2)

4. DATA ANALYSIS AND INTERPRETATION

4.1 Diagnostic test

4.1.1 Reliability Test

To measure the internal consistency of items, the study used Cronbach's Alpha which measured the six variables under study. Table 4 below revealed the test results and it was evident that all the six constructs had met the recommended reliability threshold of 0.7. Decision making agility had a Cronbach's Alpha coefficient of 0.772. This was followed by sensing agility with a Cronbach's Alpha value of 0.776. Thereafter, performance was next with a Cronbach's Alpha value of 0.817. Cultural contours fluidity had a Cronbach's Alpha value of 0.868. The other variable with the highest scores was resource fluidity that recorded a Cronbach's Alpha value of 0.900.

Table 4: Reliability test results

	No. of Items	Cronbach Alpha Coefficients	Decision rule
Performance	5	0.817	Accept
Sensing agility	5	0.776	Accept
Decision making agility	5	0.772	Accept
Resource fluidity	5	0.900	Accept
Cultural contours fluidity	5	0.868	Accept

Source; ***Researcher, (2025)***

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4.1.2 Validity Test

Table 5 below revealed the test results and it was evident that all the six constructs had met the recommended KMO and Bartlett's threshold of 0.5.

Table 5: Validity test results

	No. of Items	KMO and Bartlett's Test	Decision rule
Performance	5	0.652	Accept
Sensing agility	5	0.746	Accept
Decision making agility	5	0.670	Accept
Resource fluidity	5	0.873	Accept
Cultural contours fluidity	5	0.866	Accept

Source; ***Researcher, (2025)***

4.2 Linear Regression Assumptions

A number of linear regression assumption tests were undertaken including normality and multicollinearity.

4.2.1 Normality Test

In order to validate the hypothesis that the data set followed a normal distribution, normality test was carried out with the use of normal P-P plots. The normal P-P plot, which can be seen above in Figure 4.1, revealed that the data points fell along the diagonal line. This was shown to be the case when the plot was examined. It is possible to draw the conclusion that the normalcy assumption was verified, and as a result, the data set was suitable for use in the investigation. These findings are comparable to those that were found by Engotoit et al. (2016), who discovered that normality in a data set is present when the data points in the P-P plot are located in close proximity to the line that provides the greatest fit.

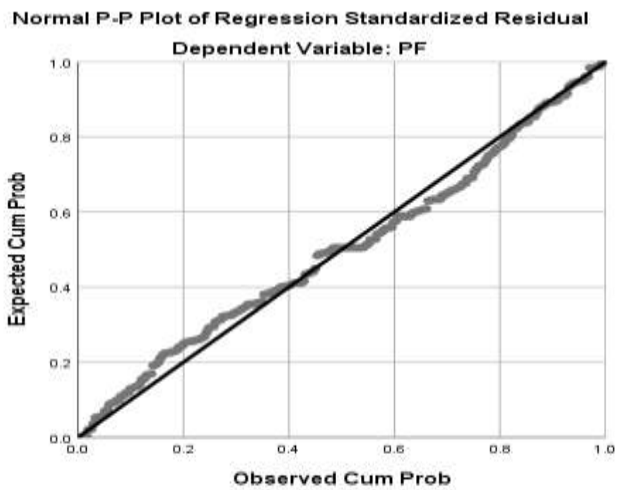

Figure 1: Normality test results

4.2.2 Multicollinearity Test

A test for multicollinearity was carried out in order to ascertain whether or not the predictor variables of the study share a significant degree of correlation with one another. In order to investigate multicollinearity, this study makes use of VIF. VIF values below 5 indicate that a predictor has a low correlation with other predictors, VIF values between 5 and 10 indicate that a predictor has a moderate connection with other predictors, and VIF values over 10 indicate that a predictor has a high and unwanted correlation with other predictors. According to the findings, the VIF values for all of the variables that were investigated are less than 5, which suggest that the dataset does not contain any instances of multicollinearity.

Table 6: Variable Inflation Factor results

	Collinearity Statistics	
	Tolerance	VIF
(Constant)		
Sensing agility	.439	2.278
Decision making agility	.397	2.520
Resource fluidity	.254	3.935
Cultural contours fluidity	.222	4.498

Source; *Researcher, (2025)*

4.2 3: Heteroscedasticity Test

The Breusch-Pagan test was utilized in order to investigate the heteroscedasticity test for residuals. The alternative hypothesis of heteroscedasticity was compared to the null hypothesis of homoscedasticity in order to determine whether one was correct. Breusch and Pagan (1979) state that the null hypothesis of homoscedasticity is accepted if the p values that correspond to the chi-square test statistics are greater than the 5 percent level of significance. On the other hand, the null hypothesis of homoscedasticity is rejected if the p values that correspond to the chi-square test statistics are less than the 5 percent level of significance. The model has no problem of heteroscedasticity or the error variance is constant since the p-value is not significant, meaning that p-value is 0.85 which is greater than 0.05. Consequently, the null hypothesis was not rejected the error variance is constant. This results are consisted with that of Kinuthia (2025).

Table 7: Heteroscedasticity results

Source	chi2	Df	Prob>chi2
Heteroscedasticity	11.105	13	.854

Source; *Researcher, (2025)*

4.2.4: Autocorrelation Test

The Durbin-Watson (DW) test result shows a value of 1.721. This statistic tests for autocorrelation in the residuals of a regression model. A DW value between 1.5 and 2.5 generally indicates no significant autocorrelation. Since the value is within this range, it suggests that there is no serious autocorrelation problem in the model, meaning the residuals are likely independent of each other.

Table 8: Autocorrelation results

Source	Prob>chi2
Autocorrelation (DW test)	1.721

Source; *Researcher, (2025)*

4.3 Correlation test

The study performed a Pearson correlation analysis to determine the strength and direction of the relationship between the independent variables and between the independent and dependent variables. Correlation between 0.1 to 0.3 indicates a weak relationship, 0.4 to 0.5 moderate relationships, and 0.6 to 0.8 a strong relationship. Based on the results, it was found that there was a strong positive and significant relationship between sensing agility and performance (0.756, p-value < 0.05). Similarly, decision-making agility was found to have a strong positive and significant relationship with performance (0.660, p-value < 0.05). Resource fluidity exhibited a weak positive and significant relationship with performance (0.330, p-value < 0.05), while cultural contours also showed a weak positive and significant relationship with performance (0.219, p-value < 0.05). Firm age was found to have a weak positive and significant relationship with performance (0.287, p-value < 0.05), while firm size also exhibited a weak positive and significant relationship with performance (0.181, p-value < 0.05).

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Table 9: Pearson correlation results

		PF	SA	DM	RF	CC	FA	FS
PF	Pearson Correlation	1						
	Sig. (2-tailed)							
	N	228						
SA	Pearson Correlation	.756**	1					
	Sig. (2-tailed)	.000						
	N	228	228					
DM	Pearson Correlation	.660**	.743**	1				
	Sig. (2-tailed)	.000	.000					
	N	228	228	228				
RF	Pearson Correlation	.330**	.377**	.458**	1			
	Sig. (2-tailed)	.000	.000	.000				
	N	228	228	228	228			
CC	Pearson Correlation	.219**	.289**	.363**	.844**	1		
	Sig. (2-tailed)	.001	.000	.000	.000			
	N	228	228	228	228	228		
	Sig. (2-tailed)	.070	.000	.001	.000	.000		
	N	228	228	228	228	228		
FA	Pearson Correlation	.287**	.222**	.213**	.129	.082	1	
	Sig. (2-tailed)	.000	.001	.001	.052	.218		
	N	228	228	228	228	228	228	
FS	Pearson Correlation	.181**	.140*	.206**	.253**	.176**	.524**	1
	Sig. (2-tailed)	.006	.034	.002	.000	.008	.000	
	N	228	228	228	228	228	228	228

Source; *Researcher, (2025)*

4.4 Regression Analysis Results

A regression analysis was conducted to determine how well the model explains the relationship between dependent and independent variables. To do this, a total of seven analytical models were run in order to draw conclusion of each model as illustrated below.

Testing control effect of firm age and firm size on performance of Manufacturing firms in Nairobi

The model summary indicates that the control variables, Firm Size (FSS) and Firm Age (FAA), together explain 57.8% of the variation in performance (PF), as shown by the R-squared value of 0.578. The adjusted R-squared of 0.574 suggests a strong model fit. The Durbin-Watson value of 1.787 indicates no significant autocorrelation in the residuals, suggesting reliable estimates.

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Table 10: Control effect model summary

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.760[a]	.578	.574	.47512	1.787

a. Predictors: (Constant), FSS, FAA

b. Dependent Variable: PF

Source; ***Researcher, (2025)***

Model 1 reveals that both firm age (FAA) and firm size (FSS) significantly predict performance outcomes. Firm age (FAA) exhibits a positive and substantial effect ($B = 0.091$; $\beta = 0.462$; $t = 7.284$; $p < .05$), indicating that for each one-unit increase in firm age, performance increases by 0.091 units, supporting the notion that older firms accumulate routines, legitimacy, and organizational learning that enhance performance (Coad et al., 2017). Similarly, firm size (FSS) is positively related to performance ($B = 0.061$; $\beta = 0.354$; $t = 5.578$; $p < .05$), aligning with studies in African SMEs that show larger firms benefit from resource slack, bargaining power, and economies of scale, leading to improved performance (Ndombi Avouba et al., 2024; Rampyapedi & Adetunji, 2024). The standardized coefficients indicate that firm age ($\beta = 0.462$) has a stronger influence on performance than firm size ($\beta = 0.354$) in this sample. The intercept value (1.878, $p < .05$) suggests a positive baseline level of performance, even before considering firm age and size. Overall, the results align with theoretical expectations, demonstrating that both experience (firm age) and scale (firm size) contribute uniquely to SME performance in dynamic environments.

Table 11: Control Effect Regression Results

	Model	Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	1.878	.096		19.581	.000
	FAA	.091	.012	.462	7.284	.000
	FSS	.061	.011	.354	5.578	.000

Source; ***Researcher, (2025)***

Testing direct effect of organization agility on performance of Manufacturing firms in Nairobi

The analytical model sought to analyze the effect of the four independent variables (sensing agility, decision making agility, resource fluidity and cultural contours) on performance of manufacturing SMEs in Nairobi. From the finding of the model summary, it was observed that R-Squared value was 0.938 or 93.8%. The result is an indication that 93.8% of performance among manufacturing SMEs is affected by sensing agility, decision making agility, resource fluidity and cultural contours.

Table 12: Model Summary for direct effect results

Model	R Square	Adjusted R Square	Std. Error of the Estimate
.968[a]	.938	.936	.18427

Source; ***Researcher, (2025)***

Hierarchical multiple regression analysis was employed to examine whether four strategic agility dimensions—sensing agility, decision-making agility, resource fluidity, and cultural contours—predict the performance of manufacturing SMEs in Nairobi. Ordinary Least Squares (OLS) alone was deemed insufficient because assuming homoskedastic, independent errors can inflate t-statistics and underestimate standard errors when those assumptions are violated; accordingly, we estimated hierarchical models with robust standard errors to mitigate heteroskedasticity and model-specification concerns (White, 1980; Wooldridge, 2010). Following best practice for incremental theory testing, Model 1 entered controls and Model 2 added the focal agility block to assess improvement in explanatory power and construct validity (Cohen et al., 2003; Hayes, 2018). Table IV reports the estimates for the direct effects. Model 1 (controls only) established the baseline fit, while Model 2 (controls + agility constructs) showed a marked improvement in explained variance and yielded positive, statistically significant coefficients for all four capabilities, indicating that the agility block meaningfully enhances both model fit and substantive interpretation (Cohen et al., 2003; Hayes, 2018).

The study tested four hypotheses (H01–H04) on the direct effects of the capability set. Model 2 shows that sensing agility is positively and significantly associated with performance ($B = 0.074$, $\beta = 0.461$, $t = 9.217$, $p < .05$), leading to rejection of H01 and aligning with theory that superior "sensing" under dynamic capabilities and strategic agility underpins advantage through earlier recognition of opportunities and threats (Doz & Kosonen, 2010; Teece, 2007; Roberts & Grover, 2012). Decision-making agility is likewise positive and significant ($B = 0.032$, $\beta = 0.183$, $t = 3.976$, $p < .05$), prompting rejection of H02 and supporting evidence that fast-but-rigorous strategic choice improves outcomes in high-velocity contexts (Eisenhardt, 1989; Doz & Kosonen, 2010). Resource fluidity shows a positive, significant relationship with performance ($B = 0.189$, $\beta = 0.180$, $t = 7.003$, $p < .05$), resulting in rejection of H03 and underscoring the value of rapid reallocation of people, capital, and assets in dynamic markets (Doz & Kosonen, 2010; Reed, 2021). Finally, cultural contours are positive and significant ($B = 0.072$, $\beta = 0.371$, $t = 8.696$, $p < .05$), leading to rejection of H04 and reinforcing long-standing evidence that adaptability, involvement, consistency, and mission are linked to organizational effectiveness (Denison & Mishra, 1995; Yılmaz & Ergun, 2008). Collectively, the hierarchical modeling confirms that each capability contributes uniquely and significantly to performance, and that introducing the agility block yields a statistically robust, substantively meaningful improvement over the controls-only baseline (Cohen et al., 2003; Hayes, 2018; Wooldridge, 2010).

Table 13: Regression Coefficient for Direct Effect

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
2	**(Constant)**	1.626	.074		22.126	.000
	FA	.011	.005	.056	2.045	.042
	FS	.010	.005	.057	2.126	.035
	SA	.074	.008	.461	9.217	.000
	DM	.032	.008	.183	3.976	.000
	RF	.189	.027	.180	7.003	.000
	CC	.072	.008	.371	8.696	.000

Source; *Researcher, (2025)*

CONCLUSION AND RECOMMENDATION

The study employed primary data and hierarchical multiple regression to test whether strategic-agility capabilities—sensing agility, decision-making agility, resource fluidity, and cultural contours—predict firm performance. The modeling strategy (controls entered in Model 1; focal capabilities in Model 2 with robust standard errors) revealed that all four capabilities exhibit positive and statistically significant associations with performance, leading to rejection of the respective null hypotheses. Substantively, the evidence affirms that organizations which detect environmental shifts earlier (sensing), commit to timely and disciplined choices (decision agility), redeploy people, capital, and assets rapidly (resource fluidity), and sustain enabling cultural traits (adaptability, involvement, consistency, mission) realize superior outcomes in volatile contexts (Doz & Kosonen, 2010; Teece, 2007; Roberts & Grover, 2012; Denison & Mishra, 1995; Yılmaz & Ergun, 2008; Eisenhardt, 1989). These results cohere with dynamic capabilities and strategic agility theory, which argue that sensing, seizing, and reconfiguring constitute mutually reinforcing microfoundations of performance in turbulent markets.

The findings suggest that policymakers and practitioners in Nairobi's manufacturing ecosystem should prioritize a balanced capability agenda. For managers, institutionalizing outside-in sensing routines, codifying fast-but-rigorous decision protocols, investing in cross-training, modular processes, and flexible supplier portfolios, and intentionally shaping learning-oriented cultures can translate uncertainty into advantage (Eisenhardt, 1989; Doz & Kosonen, 2010). For public and meso-level actors (industry associations, TVETs, standards bodies), targeted support for market-intelligence access, executive education on decision speed and quality, supplier-development partnerships, and lean/Kaizen extension services can accelerate diffusion of these practices across SMEs. Because performance payoffs rise with volatility, instruments that raise resilience—early-warning information, sandboxed process trials, and financing aligned to reconfiguration—will further amplify the returns to firm-level capability building (Wilden, Gudergan, Nielsen, & Lings, 2013; Reed, 2021).

This study offers actionable insight into how agility capabilities drive performance, yet it has limitations. Cross-sectional data constrain causal claims and may capture transient effects rather than durable capability advantages. Self-reported measures raise common-method concerns despite model controls, and focusing on a single urban region may limit external validity to other sectors or counties. Although hierarchical OLS with robust errors mitigates some inferential risks, unobserved heterogeneity and potential endogeneity (e.g., managerial quality, access to finance) may still bias estimates. Finally, aggregate firm-level measures may mask micro-foundations at the team or process level through which culture, sensing, and reconfiguration actually operate.

Future research should deepen causal identification and micro-level understanding. Longitudinal designs can track capability investments, routine adoption, and lagged performance effects across business cycles; quasi-experimental approaches (natural experiments, difference-in-differences) can separate capability effects from confounds. Multi-level studies linking top-team dynamics, middle-management decision rights, and frontline behaviors to firm outcomes would unpack micro-foundations. Measurement work that digitizes operational micro-metrics (changeover times, cross-skill depth, supplier substitution lead times) can illuminate mechanisms of resource fluidity. Finally, moderated-mediation models that test how innovation rate, defect reduction, or cycle-time compression mediate the capability–performance link—under varying market dynamism—would specify how and when agility pays off in Nairobi's manufacturing context (Teece, 2007; Doz & Kosonen, 2010; Eisenhardt, 1989).

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