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Artificial Intelligence and Organizational Performance of Steel Manufacturing Firms in Kiambu County, Kenya

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Abstract

Steel manufacturers in Kenya have been facing stiff competition from imports, and most of them continue to operate production lines that depend heavily on manual labor. Digital technology can help alleviate the competitive pressure, but there is not much information on how AI can contribute to the performance of the steel firms. This study sought to investigate the impact of AI on the organizational performance of steel manufacturing firms in Kiambu County, Kenya. It was anchored on the Technology Acceptance Model while the Resource Based View and Socio Technical Systems Theory were used to interpret the findings. The study adopted a descriptive design where a questionnaire was distributed to all 125 management, supervisory and operational staff in the target firms. Overall, 110 questionnaires were returned, representing an 88% response rate. The scales were reliable, with Cronbach's alpha of 0.917 for AI and 0.892 for organizational performance. The use of AI was moderate overall ($M = 3.47$, $SD = 0.81$). AI had a positive correlation with organizational performance ($r = .458$, $p < .001$) and the simple linear regression analysis demonstrated that there was a positive and statistically significant relationship between these variables ($B = 0.400$, $t = 5.349$, $p < .001$). AI was able to explain 20.9% of the variance in the organizational performance ($F(1, 108) = 28.610$, $p < .001$), thus the null hypothesis was rejected. From the open-ended questions, high cost of technology (62.2%), inadequate digital skills (55.1%) and unreliable electricity and internet connections (48.0%) were the major challenges. The study finds that AI improves organizational performance in steel companies, although its full benefit cannot be realized yet because of the current level of adoption. Companies need to adopt AI for maintenance, planning and quality control and train their employees, while policy makers need to lower the cost of digital equipment.

Keywords: *Artificial intelligence, organizational performance, digital transformation, steel manufacturing firms, Technology Acceptance Model, Kiambu County, Kenya.*

1.1 Introduction

Artificial intelligence is no longer confined to laboratory settings. Firms use AI to plan manufacturing, identify defects and forecast demand for their products. According to Russell & Norvig (2021), AI is concerned with agents that perceive their environment and take actions to achieve certain goals. In a business setting, this typically implies software that analyzes data and either forecasts a result, suggests an action or makes a decision. Davenport & Ronanki (2018) classified business applications of AI into process automation, cognitive insights based on data and cognitive engagement with customers and employees. The three groups correspond to the topics covered in this study, including AI in operations, process automation, and AI in customer service.

Steel is a challenging industry in which to implement such technology. The industry operates with heavy machinery and high temperatures with very tight tolerances, where a fault that is overlooked for a few minutes will result in scrap, downtime, or safety issues. Technology such as sensors and analytical models may notify about a malfunction of the part before it causes the line to come to a halt, while quality models may inform about substandard material before it leaves the premises. According to Branca et al. (2020), steel is one such industry where digitalization can increase efficiency and sustainability.

Similar findings are reported in the broader literature on digital transformation. According to the review conducted by Vial (2019), digital transformation involves a change in the organization and its strategies as a result of using digital technologies. Brynjolfsson and McAfee (2014) have discussed that automation and machine intelligence are transforming how companies generate value. The technologies falling under the category of Industry 4.0, which include artificial intelligence, the internet of things, and data analytics in manufacturing industry, have resulted in effective monitoring, product quality, and cost management (Frank et al., 2019; Schwab, 2016). However, Branca et al. (2020) state one more requirement for the steel industry.

That condition is a reminder that there is no such thing as automatic benefits. Both Teece (2018) and Chesbrough (2019) assert that the success depends on committed leadership, people with the necessary skills, and an organization that is ready to change. Mhlanga (2021) revealed that AI increases efficiency and decision-making in Africa, although poor infrastructure and lack of technical skills hinder its adoption. Steel industries in Kenya are confronted with similar problems, with many relying heavily on manual labor.

Organizational performance is the dependent variable in this study. It has been conceptualized broadly, covering an organization's ability to control costs, maintain operational efficiency, and sustain sales volume. Managers in manufacturing organizations keep a close eye on all these factors, and thus, it would be appropriate to use them. Additionally, these measures do not depend on the financial statements of organizations, which may not be available for privately held organizations.

Kenya is a fitting place to pose the question. According to the Kenya National Bureau of Statistics (2023), manufacturing plays an integral role in the country’s economic development and employment creation. In addition, steel plays an integral role in the country’s construction and infrastructural activities. Nonetheless, the Ministry of Industrialization, Trade and Enterprise Development (2020) indicates that many steel producers continue to employ inefficient production processes. Vision 2030, the Big Four Agenda, and the Bottom-Up Economic Transformation Agenda, which is part of the Fourth Medium Term Plan between 2023 and 2027, are all hinged on

efficient manufacturing. Additionally, according to the United Nations Industrial Development Organization (2022), digital technology can help minimize waste and support clean production.

This study sought to find out how much impact AI has on the organizational performance of steel manufacturing organizations based in Kiambu County. The data in this study was collected through a broader study of four digital transformation strategies but analysis in terms of AI is provided herein. This paper will begin by looking at the theory and prior literature followed by methodology, results, discussion, and conclusion.

1.2 Statement of the Problem

Firms elsewhere that have adopted new digital technologies for production and management have experienced higher productivity, reduced operational costs, and improved competitiveness (Brynjolfsson & McAfee, 2014). Steel producers in Kenya have not moved out of the conventional ways of manufacturing, which rely heavily on manual practices (Ministry of Industrialization, Trade and Enterprise Development, 2020). The specific problem is that steel producers in Kiambu County continue to use manual and disjointed production processes and the contribution of AI to organizational improvement has not been established.

This impacts all levels of the organization. The management struggles with high costs of production and small margins due to competition from imported steel and local production of steel. The supervisors monitor the production processes manually, so problems with quality are identified later. The operational employees have routine manual jobs without any IT means and training. All these factors together are associated with inefficiency, poor productivity, lack of innovation, and poor competitiveness. The issue is not purely technical. It is possible that an organization possesses sensors and software but will not get much out of it if its employees either do not trust the results or do not know how to work with them. That is why the research focuses on the human factor when it comes to artificial intelligence and considers training and infrastructure along with performance.

Earlier studies show that digital technologies enhance organizational performance; however, they have failed to settle this issue owing to three limitations. They were conducted in advanced countries with developed digital infrastructure (Vial, 2019), meaning their findings might not be applicable to Kenya. In addition, Kenyan studies have been carried out in the services industry, including the banking industry (Omondi & Ayo, 2020) or even manufacturing sector in general and on capabilities such as information technology capability (Gitau et al., 2022). On the other hand, the closest Kenyan study on AI technologies is Anitah et al. (2019) where the researchers only considered two big consumer goods manufacturers. Moreover, studies in the manufacturing industry have focused on measuring the adoption rate of technologies but not on their contribution to performance and no study has been done on the impact of AI on the performance of steel manufacturers in Kiambu County. It is this gap which this study seeks to fill. In particular, it seeks to quantify the influence of AI on firm performance, as reflected in terms of production costs, efficiency, sales, productivity, and competitiveness, as perceived by managers, supervisors, and workers, through simple linear regression analysis. The result will be of importance to policymakers and to companies operating within the steel industry.

1.3 Objective of the Study

To determine the influence of artificial intelligence on the organizational performance of steel manufacturing firms in Kiambu County, Kenya.

1.4 Research Hypothesis

H_0: Artificial intelligence has no significant influence on the organizational performance of steel manufacturing firms in Kiambu County, Kenya.

2.1 Theoretical Framework

2.1.1 Technology Acceptance Model

Davis (1989) proposed the Technology Acceptance Model to understand reasons for adoption and acceptance of new technology at workplaces. It is based on two beliefs. Perceived usefulness is the degree to which an individual believes that the technology improves his performance while perceived ease of use is the degree to which an individual believes that the technology will be easy to use. As per Davis (1989), both beliefs affect attitudes and intentions, and intentions affect usage behavior, and the usefulness affects usage more strongly.

The model has undergone many adaptations. Venkatesh and Davis (2000) modified it by incorporating the role of social influences and the process of cognition in terms of job relevance and output quality as factors driving perceived usefulness. In another modification, Venkatesh et al. (2003) integrated TAM with other competing models into a single theory of unified acceptance which included effort expectancy, performance expectancy, social influences and facilitating conditions. Performance expectancy is similar to perceived usefulness and effort expectancy is similar to ease of use. Facilitating conditions like training, technical support and supportive infrastructure are very important in Kenyan steel plants, where technical support is lacking.

The TAM theory accounts for acceptance at an individual level, and any performance improvement is an inference drawn from the usage pattern of the technology. This is indeed a significant limitation of the theory, and hence, two more theories are considered to interpret the findings. The Resource Based View of Wernerfelt (1984) and Barney (1991) provides an account of how artificial intelligence systems, and the knowledge required to use such systems, can act as valuable resources which are difficult to imitate by competitors. Socio Technical Systems Theory of Trist and Bamforth (1951) accounts for the reasons why the usefulness of any technology depends upon its compatibility with the surrounding human, technical and procedural context.

2.1.2 Application of the Technology Acceptance Model to the Hypothesis

In steel plant operations, AI facilitates predictive maintenance, quality control, production planning, and faster decision making. All these processes require from the employees something new: reading the results, trusting them and adjusting their behavior. In accordance with the Technology Acceptance Model (TAM), the employees will adopt these technologies as soon as they realize that these technologies minimize errors, accelerate decision making and ensure proper operation of equipment, as well as are user-friendly. It is clear that bad training or inadequate design of technologies will affect adoption and thus productivity.

There are two propositions derived from TAM in this case. First, the greater perceived usefulness of AI among employees is associated with its higher adoption and better performance of the organization. Second, barriers to ease of use, including skill deficiencies and unstable infrastructure, hinder this relationship. Null hypothesis is tested for the first proposition, while the second one is discussed in light of the findings related to training of the employees and barriers identified in open-ended questions. If TAM is correct, H01 should be rejected and the relationship should be positive.

2.2 Empirical Review

Evidence from other parts of the world shows a consistent relationship between AI and performance in the positive direction. Brynjolfsson and McAfee (2014) show that firms using machine intelligence become productive, coordinating processes and being responsive to the market. According to Vial (2019), AI-driven digital transformation improves efficiency and performance of business due to decision-making based on data. Wamba-Taguimdje et al. (2020) conducted research of 500 cases of AI-driven transformation initiatives and discovered that such initiatives lead to creation of business value measurable in terms of performance at the level of process and organization. Mikalef and Gupta (2021) conducted a survey of firms and discovered that AI capability which includes data, skills and organizational resources results in greater creativity and firm performance. The common feature is that AI brings benefits when it is embedded in the organizational capability and not just purchased.

Manufacturing studies illustrate where the benefits emerge. According to Frank et al. (2019), as well as Schwab (2016), the advantages of AI are connected to its ability to facilitate predictive maintenance, quality control, production planning and monitoring, thereby reducing operating costs and increasing efficiency. In addition, according to Bharadwaj et al. (2013), digital business strategy, enhanced by sophisticated analytics and decision-support systems, helps increase efficiency, innovate and gain competitive advantages. Regarding the steel industry, the positive impact of the digital technologies has been identified by Branca et al. (2020). They noted that digitalization is able to make production more efficient and sustainable, though the skills of the workforce should be constantly improved.

It helps to think of three ways AI has an impact on performance. The first one is better decision-making. According to Davenport and Ronanki (2018), cognitive insights are based on algorithm-based identification of patterns in large amounts of data, which in case of a steel plant means demand forecasts, production runs or furnace and rolling schedules. The second way is automation, which automates routine manual checks and data entry, minimizes errors, and makes room for highly qualified employees to make decisions. The third way is customer engagement, where AI software provides responses to customers' questions, tracks orders and gathers their feedback. All three ways correspond to an indicator in the current study, and they all have potential to reduce cost, increase efficiency or generate sales.

Africa is no exception to this evidence of advantages and challenges. According to Mhlanga (2021), artificial intelligence is efficient and enhances decision making in African firms, yet faces challenges such as poor infrastructure and lack of technical skills. Afolayan et al. (2022) indicated that technologies of Industry 4.0 are associated with better manufacturing performance in Africa, yet their implementation is hindered by high costs, poor digital infrastructure and skills. Both arguments corroborate the TAM claim about the role of ease of use and readiness in technology performance.

Several researchers warn that technology on its own achieves nothing. Westerman et al. (2014) stated that digital transformation is successful when technology is coupled with people and processes, and this is driven by vision, while Teece (2018) and Chesbrough (2019) highlight leadership, dynamic capabilities and readiness as the conditions that will make investment translate to performance. Such literature would lead one to anticipate a positive yet partial link between AI and performance because there are other factors in organizations that matter too.

For Kenya, there is even less direct empirical evidence. In a study by Anitah et al. (2019), two large scale manufacturers were investigated and the application of Industry 4.0 solutions like big data analytics and robots enabled improvement in performance due to better demand forecasting, fewer errors, and more flexibility. The research was only conducted among two consumer goods manufacturers and did not look into steel industries. Hence the results cannot directly be applied in Kiambu County. Another study by Gitau et al. (2022) showed that information technology infrastructure capability positively impacted the performance of manufacturing firms in Nairobi City County. The research, however, measured IT capability in general but not AI. Kipkirui (2024) in his survey conducted among manufacturing firms in the Nairobi region identified that technological, organizational, and environmental factors accounted for 47.5 percent variance in the adoption of digital transformation. Muthoni and Kinyua (2021) and Wanjiku and Omwenga (2022) noted that digital technologies boost efficiency, control, decision making, and competitiveness of Kenyan manufacturers, though their research did not specifically focus on the use of digital technologies. Other than the manufacturing sector, Omondi and Ayo (2020) established that digital technologies increased efficiency and customer service in Kenyan banks, thus showing the nature of the effect but not the magnitude in heavy industry.

Three major weaknesses run through this body of literature. First, the research on AI is drawn from either advanced economies or service sector. Secondly, the Kenyan manufacturing literature on digital technologies uses a combination of digital technologies or focuses on a single firm. Thirdly, there is no attempt to isolate the effect of AI on organizational performance in steel manufacturers. In this regard, this study attempts to examine the influence of AI on organizational performance in steel manufacturers in Kiambu County through a census of employees at three organizational levels.

Taken as a whole, the literature suggests a directional hypothesis. Given that AI enables firms to make informed decisions, minimize errors, and respond quickly to customers, firms that adopt AI are expected to perform better in cost control, efficiency and sales. The hypothesized relationship is positive and is tested against a null hypothesis of no significant influence.

3.1 Methodology

The study used a descriptive research design with a quantitative orientation. The design was suitable for achieving the objective as it describes how firms conduct themselves without changing the existing setting and enables the testing of the two variables statistically. According to Mugenda & Mugenda (2003), descriptive designs are suitable for collecting information related to organizational practices and behaviors. A bit of qualitative data was also collected through open-ended questions in the same questionnaire to help explain the figures. As Creswell (2014) and Leedy and Ormrod (2021) point out, mixing the two sources enhances the credibility of findings and their completeness. The data collection was based on a larger study of four digital transformation strategies with only the one related to artificial intelligence covered in this case.

The target population was 125 employees of steel manufacturing companies in Kiambu County, selected from company staff list obtained from the management of the firms that participated in the study. It comprised senior and middle managers, supervisors and the actual users of the technology, which ensured that all the departments using the digital tools were covered, including production, quality control, information technology and sales. Since the population was small and defined clearly, the survey used a census approach, whereby the sample size was the total population of 125 respondents. According to Mugenda and Mugenda (2003) and Kothari (2004),

a census eliminates sampling error and gives all eligible participants an equal opportunity of being included. In addition, views from decision makers regarding technology purchase, supervisors who monitor its usage and employees who use the technology daily are likely to vary, since they perceive it differently. A separate pilot study involved 13 respondents, about 10 percent of the population, who were not included in the main survey.

Primary data was collected using a structured questionnaire, which is an efficient way of collecting standard information from a large number of people within a short period of time according to Kothari (2004). The questionnaire was administered by the human resource or administration department of each firm after management approval, and respondents filled it out on their own time. Follow-up reminders were sent to increase the response rate. Closed questions involved a five-point Likert Scale ranging from 1 (strongly disagree) to 5 (strongly agree). Artificial Intelligence was measured using five items (AI1 to AI5), while organizational performance was measured using five items (OP1 to OP5). According to Kothari (2004), a mean score of 3.50 and above meant high agreement; a score from 2.50 to 3.49 meant moderate agreement, and a score below 2.50 meant low agreement. There were three open-ended questions asking about the challenges of implementing digital transformation, methods for improving organizational performance and any other comments.

The pilot made use of the same questionnaire under almost identical circumstances. The respondents were allowed to state the degree of clarity of items, the appropriateness of the language and time required, which was another way of testing face validity. Content validity was achieved through university supervisors assessing whether all variables had been considered and items corresponded with the objectives (Kothari, 2004). The construct validity of the questionnaire could only be established after conducting the main data collection and calculating corrected item total correlation coefficient, where a value of 0.30 or more means that an item is measuring the same construct as other items in the scale (Field, 2018). Reliability of the questionnaire was calculated using Cronbach's Alpha coefficient, where a value of 0.70 or more shows acceptable internal consistency (Nunnally, 1978).

The data set was preprocessed through cleaning, coding and screening for missing values and outliers prior to analyzing it using SPSS. Respondents' characteristics and opinions on AI were described in terms of frequencies, percentages, means and standard deviations. Skewness and kurtosis tests were employed to determine the normality of the distribution, whereby the values ranging from -2 to 2 indicated approximate normality (George & Mallery, 2010). The relationship between AI and organizational performance was assessed with the help of the Pearson correlation. Given that there was only one independent variable in the objective, a linear regression model was employed:

$$\hat{Y}(OP) = \beta_0 + \beta_1 AI + \varepsilon.$$

In this model, $\hat{Y}(OP)$ represent predicted organizational performance; β_0 is the constant; β_1 is the regression coefficient, and ε is the error term. R^2 and the ANOVA F test were used to evaluate the model fit, whereas the t test was employed to assess the significance of the regression coefficient.

The simple linear regression model relies on the assumptions that the relationship is linear, that the errors are normally distributed and that the observations are independent. These assumptions were tested using the correlation test, the skewness and kurtosis test and the design of data collection where individual respondents answered the survey. Since individual respondents evaluated both the variables, common method bias exists, and it is recognized as a limitation in

section 6.3. Open-ended questions were analyzed using thematic analysis as discussed by Braun and Clarke (2006).

Table 1: Operationalization of Study Variables

Variable	Indicators	Measurement	Analysis
Artificial intelligence (independent)	Use of AI, automation of processes, AI in customer service	Five-point Likert scale, mean of items AI1 to AI5	Mean, SD, Pearson r, simple linear regression
Organizational performance (dependent)	Production cost, operational efficiency, sales volume, productivity, competitiveness	Five-point Likert scale, mean of items OP1 to OP5	Dependent variable in the regression model

4.1 Results and Discussion

4.1.1 Response Rate and Respondent Profile

All 13 questionnaires were returned in the pilot study. In the actual study, out of the 125 questionnaires that were handed out, 110 were returned as usable, representing a response rate of 88.0%. According to Mugenda & Mugenda (2003), any response rate above 70% is excellent for analysis and reporting purposes, thus the above-mentioned response rate exceeds the benchmark. All analyses presented hereafter are based on the 110 respondents.

4.2 Descriptive Findings on Artificial Intelligence

Table 2 depicts the results of respondents' perceptions towards AI. The mean value for all questions was 3.47 (SD = 0.81), placing it in the moderate category. The use of AI technology by the companies studied is evolving but has not become part of daily routine yet. There were two items that were in the high category, namely, that AI lowers manual production errors (M = 3.52, SD = 0.89) and increases the speed of decision-making (M = 3.51, SD = 0.96). Predictive maintenance was close behind with M = 3.46. The two lowest-ranked categories were staff training (M = 3.43) and customer service (M = 3.41). Standard deviations ranged from 0.86 to 1.02, resulting in coefficients of variation of 24.9%-29.9%. Perceptions towards customer service were the most volatile, suggesting that there is greater variability in experience of using AI in customer service than in manufacturing. The five means differ only by 0.11 points, indicating that the companies are at a similar level of adoption of the technology. Taking each item individually, the findings indicate a certain aspect about the use of AI in steel companies. Increased speed and accuracy of decision-making are some of the advantages that can be realized within days by a shift supervisor, especially when an alarm from a monitoring system helps avoid a halt. The value of predictive maintenance will be evident within several months since there is no way to measure those breakdowns that have not occurred.

Table 2: Descriptive Statistics for Artificial Intelligence

Item	Mean	SD	Interpretation
AI improves decision making speed	3.51	0.96	High
AI reduces manual production errors	3.52	0.89	High
AI enhances predictive maintenance	3.46	0.86	Moderate
AI improves customer service response	3.41	1.02	Moderate
Staff are trained to use AI tools	3.43	0.95	Moderate
Overall Mean	**3.47**	**0.81**	**Moderate**

This corresponds with TAM. The employees were most positive about where the usefulness of AI was easily observable, which was in fewer manual errors and quick decisions, and only those two achieved a high rating. This is consistent with the findings of Brynjolfsson & McAfee (2014) and Vial (2019) concerning the role of AI in increasing productivity and sharpness in decision-making. Staff training, which got a relatively low rating, is relevant to the second proposition of TAM. According to Branca et al. (2020), the digitalization of steel production increases efficiency but requires constant upskilling, and the rating of 3.43 implies that this requirement is not entirely fulfilled in Kiambu County. The facilitation conditions of Venkatesh et al. (2003), which comprise not only staff training but also technical support and infrastructure, can provide another interpretation. If there is a lack of facilitation conditions, the employees might find the AI useful, in theory, but difficult to use in practice, and the level of use will remain shallow. Poor infrastructure and lack of technical skills are considered by Mhlanga (2021) as barriers to AI in Africa; this could explain why adoption is at the moderate rather than the high level.

4.3 Correlation Analysis

The Pearson correlation indicated that there was a positive and significant relationship between AI and organizational performance ($r = .458$, $p < .001$). According to the general criteria by Cohen (1988), this is considered a moderate correlation. Firms that reported higher levels of AI use also reported higher organizational performance. This is consistent with the TAM prediction that perceived usefulness results in use and use results in outcomes, and it is consistent with the positive direction found by Wamba-Taguimdje et al. (2020) and Mikalef and Gupta (2021). It should be noted that the strength of the correlation should not be overemphasized. An r value of .458 indicates about 21% shared variance; therefore, much of the variance in performance remains unexplained. This is common in organizational research because performance depends on many factors simultaneously such as market situation, input costs, leadership, and competition from imports, and it is reasonable for one technological innovation to explain only a part of variance. Correlation does not imply causality; therefore, regression analysis was conducted to quantify the relationship.

4.4 Regression Results

The simple linear regression of organizational performance against AI is provided in Table 4. This relationship was statistically significant ($F(1, 108) = 28.610$, $p < .001$). The independent variable (AI) accounted for 20.9% of the variance of organizational performance ($R^2 = .209$, adjusted $R^2 = .202$), with the standard error of the estimate being equal to 0.634. The regression equation for

predicting the organizational performance variable was $\hat{Y}(OP) = 2.209 + 0.400(AI)$. The coefficient value of AI was positive and significantly different from zero ($B = 0.400$, $SE = 0.075$, $t = 5.349$, $p < .001$); with the 95% confidence interval being [0.251; 0.549]. A one-point increment in the mean score of AI was, hence, associated with a 0.400-point increment in the mean score of organizational performance. From a data dispersion viewpoint, an increment by one standard deviation in AI (0.813) would yield an improvement of about 0.325 points in performance.

Table 4: Simple Linear Regression Results

Statistic	Value
R	0.458
R squared	0.209
Adjusted R squared	0.202
Standard error of estimate	0.634
F(1, 108)	28.610, $p < .001$
Constant	2.209
B (artificial intelligence)	0.400
Standard error of B	0.075
t	5.349, $p < .001$
95% confidence interval for B	0.251 to 0.549

An illustration demonstrates the meaning of the equation. A firm giving AI a rating equal to the sample mean of 3.47 should be rated approximately 3.60 on organizational performance. A firm giving AI a rating one standard deviation above the mean, or approximately 4.28, should be rated approximately 3.92, while a firm giving AI a rating one standard deviation below the mean, or approximately 2.65, should be rated 3.27. A difference of about 0.65 points between the lower and higher firms is significant on a five-point scale.

The effect is significant in both a substantive and in a statistical sense. The explained variance/unexplained variance ratio leads to an effect size of $f^2 = 0.26$ on the Cohen scale (1988), which falls somewhere in between the standard medium (.15) and large (.35) benchmarks. The confidence interval remains sufficiently away from zero to ensure adequate precision.

The finding corroborates the Technology Acceptance Model. When employees find that AI technology is useful in decision making, minimizing errors and predictive maintenance, then its adoption will lead to greater benefits in terms of costs, efficiency, and sales. It supports Brynjolfsson and McAfee (2014) and Vial (2019), who established that transformation driven by AI leads to productivity and decision-making improvements, and Wamba-Taguimdje et al. (2020), whose extensive sample of cases demonstrated performance benefits resulting from adoption of AI technology on both process and organization levels. It also corroborates Mikalef and Gupta (2021), who observed that firm's AI capability positively correlates with firm performance. In steel industry, it confirms the findings of Branca et al. (2020), who observed efficiency gains due to digitization of steel production processes. In Kenya, it extends the operational benefits that have

been established for Industry 4.0 technologies in two big firms by Anitah et al. (2019) to an industry that had not been researched before.

Resource Based View provides another interpretation. Barney (1991) suggested that resources generate an advantage if they are valuable and rare, and hence, the moderate level of use of AI by organizations operating in Kiambu County shows that these companies have not yet gained the capability which would make AI such a valuable and rare resource. Socio Technical Systems Theory (Trist & Bamforth, 1951) provides yet another perspective, because the low level of scores related to staff training shows that the fit between AI and skills of employees is not perfect yet. Both perspectives shed light on the reasons for a positive impact already achieved despite a moderate level of adoption.

The AI variable accounted for 20.9% of the variation in performance, leaving 79.1% unaccounted for. Leadership commitment, organizational culture, and employee capability are factors influencing how much digital technology helps improve performance, according to Teece (2018) and Chesbrough (2019), and they may explain some of the rest. The model considers AI in isolation; because of the overlap in variation between AI and the other digital strategies, some of the coefficient could be attributed to their combined effect. None of these considerations undermines the primary conclusion. The use of a single predictor variable accounted for about 20% of the variation in performance, and it was evident in the correlation and regression results. As far as a manager is concerned, the takeaway is that AI is among the tools available and that they complement each other.

4.5 Qualitative Evidence

The open-ended questions about digital transformation generally, including the use of AI, and they give an explanation of the quantified data. Out of the 98 participants who cited some challenges, 62.2% cited the expensive nature of technology as the main challenge. For instance, one participant stated: "The machines and software are expensive and we cannot upgrade every year." This corresponds to the moderate adoption rate stated above. Lack of adequate digital competencies was mentioned by 55.1% as captured in the statement: "Many of our operators were not trained to use the new systems." This corresponds to the moderate staffing training rate mentioned above, and the TAM theory, which mentions ease of use. The unreliable power supply and Internet connection were cited by 48.0% as shown in the statement: "When power or internet goes off, the monitoring system stops."

The comments were also very pragmatic. Participants did not question the value of the digital technology in general. What they questioned was the company's ability to afford it, employees' abilities to apply it, and the plant's capability to maintain it, and these were matters of readiness, not of willingness. This is a useful categorization because readiness can be increased by making appropriate investments and developing appropriate policies, while unwillingness is much more difficult to alter.

Among the 92 respondents who provided ways to improve performance, 63.0% recommended training and upskilling, 53.3% recommended investments in technology infrastructure, and 40.2% recommended strong commitment from top management, which, as one of the respondents stated, means "Management should set a clear digital plan and fund it." This directly addresses the barriers mentioned above, and the recommendations are in agreement with Barney (1991), who argues that technology increases performance when used in combination with skilled people and proper leadership. In the final question, out of 54 respondents, 50.0% recommended that digital

transformation is necessary, as one of the respondents said, "Steel firms that do not go digital will lose customers." Additionally, 35.2% recommended policy support, such as, for example, "Government should give tax relief for digital equipment," and 25.9% recommended that returns take time and are difficult to measure.

The three key barriers may also be interpreted with respect to the theories underlying the study. Cost is linked to Resource Based View, because companies lacking financial resources are less likely to develop the AI competence required for the technology to become a source of sustainable competitive advantage. Lack of skills is associated with both TAM and STS, because lack of training makes it harder for employees to use the technology, and the alignment between the technical and social systems is still weak. Power and connectivity problems represent facilitating conditions in the terminology of Venkatesh et al. (2003). They affect perceived usefulness of the technology, when a monitoring system does not work at the very moment when it is needed. All the three barriers reinforce each other; therefore, it is unlikely that a single intervention such as acquisition of equipment will suffice. In general, companies appreciate the potential of the digital technology, but are constrained by cost, skills and infrastructure. This explains, among others, the moderate level of AI adoption and reasonable, yet not full explanatory power of the regression analysis.

4.7 Hypothesis Testing

Table 5: Summary of Hypothesis Testing

Hypothesis	Decision	Evidence
H0: Artificial intelligence has no significant influence on organizational performance	Reject H01	$B = 0.400$, $t = 5.349$, $p < .001$; $R^2 = .209$; $F(1, 108) = 28.610$, $p < .001$

The null hypothesis was rejected owing to the fact that there was a significant impact of AI on the performance of organizations at the 5% significance level. Artificial Intelligence thus significantly and positively impacts the performance of the steel manufacturing companies in Kiambu County. This finding is uniform across the different types of data collected in this study. There was positive and significant correlation, a positive and significant regression with a confidence interval that did not include 0 and an interview response that emphasized the role of digital technology to competition although its impact would be late. While such congruity adds to the reliability of the conclusion, it is worth noting that the finding is based on cross-sectional data from employees perceptions.

5.1 Conclusion

The research aimed at identifying the effect of artificial intelligence on the organizational performance of steel manufacturing companies in Kiambu County. The respondents agreed most that the adoption of AI minimizes mistakes in production and enhances decision-making process and agreed the least that the employees are well-trained in using it and in enhancing customer service response. There was a significant and positive correlation between AI and organizational performance. Furthermore, AI significantly affected organizational performance with $B = 0.400$, $p < .001$, and the variance explained by AI was 20.9%. Thus, the null hypothesis is rejected. The current research shows that AI positively impacts the organizational performance of steel

manufacturing enterprises and that its considerable potential can be exploited even at the current moderate adoption rate. The reasons for poor adoption were high cost, insufficient digital skills, and instability of power supply and internet connection. In terms of the Technology Acceptance Model, the advantages of AI became obvious in cases where people considered it to be beneficial, thus supporting the results from the readings of the Resource Based View and the Socio Technical Systems Theory.

The study makes three important contributions. First, it provides context-specific data on AI application from the steel manufacturing sector which is a sector that had not been considered before by previous Kenyan researches. Second, it assesses the performance impact of AI rather than just looking at the adoption rate. Third, it relates the figures to theoretical framework as well as to the impediments perceived by the firms, thus giving managers and policymakers an operational base.

6.1 Recommendations

The management of steel manufacturing companies should be encouraged to invest in AI and take it further than what it does currently. AI was most strongly associated with reduction of manual errors and speed of decision making; hence companies should capitalize on these benefits through taking AI from predictive maintenance into production planning and quality control where early detection of faults will reduce wastage. Training should be considered an integral component of each AI investment. The fair training rating, together with the worry about skills raised by 55.1% of respondents, indicates that ease of use is indeed a constraint. Training should be ongoing for operators, supervisors, and managers using the software being used. Management should also develop a budgeted digital strategy with measurable goals, and measure the returns from AI investments since this was noted by respondents to be slow and difficult to measure.

Firms should ensure that the infrastructure necessary for the operation of AI technologies is secured. The cost of backup power, strong internet connections, and data protection should be accounted for along with the cost of technology itself, since 48.0% of the respondents mentioned unstable power and poor connectivity as a potential problem. AI should be implemented in the areas of work that face customers, like orders tracking and inquiry responding, as these are the operations with the poorest evaluations and most disagreements in opinions. The introduction of AI should be performed gradually. One way to do it is to begin with the pilot line where the use of AI in predictive maintenance and product quality checks is tested, followed by measuring the impact of implementation on downtime, waste, and costs per unit, and then expanding implementation to other lines after proving success.

In regard to the policy recommendation, the Ministry of Industrialization, Trade and Enterprise Development together with the Kenya Association of Manufacturers can use tax incentives and exemption from duties on imports of digital equipment due to the high cost being the main constraint. The government can also ensure that there is support of digital skills acquisition via collaboration between the industries and the universities. In addition, government should ensure that there is increased access to reliable electricity and Internet facilities in the industrial zones like in Kiambu County. Setting up of goals of adoption of digital in the steel sub-sector within the manufacturing strategy would ensure that the recommendations are aligned with vision 2030 and the Bottom-Up Economic Transformation Agenda. The industry association can also help in gathering experiences from the firms that have adopted AI in order to assist the small-scale plants.

6.2 Implications for Theory, Policy and Practice

As for theory, the research confirms the Technology Acceptance Model within the framework of heavy industries in developing countries while previous studies on the topic considered office software and service organizations only. The positive and significant effect of AI as well as the connection between moderate training evaluations and moderate adoption confirm that the concepts of usefulness and ease of use remain relevant for understanding of the transformation of AI to organizational outcomes. In addition, the current study proves that TAM should be complemented by other theoretical approaches. The Resource Based View assists in the explanation of the fact that capabilities but not the possession of technologies make companies competitive.

For policy makers, the evidence gathered from Kiambu County provides clear data at the firm level about the relationship between AI and performance in the steel industry. This evidence can be used to justify any incentives and training programs. The technical colleges and universities that provide education for manufacturing industries can develop short courses in industrial data analysis, predictive maintenance, and the management of automated systems. This will ensure that there is a match between the skills required by the firms and the skills available. In terms of practice, the outcomes indicate that AI deserves the attention of steel managers; however, its success will depend on training, solid infrastructure, and managerial commitment. Companies that allocate investments only in machines will not get the same benefit as companies that invest in both machines and people.

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