

Artificial Intelligence Integration, Remote Work Arrangements and Employee Performance in Manufacturing Firms in South-East Nigeria

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Abstract

The spread of artificial intelligence (AI) tools across workplaces has raised questions about how such technologies shape employee performance, particularly where they coincide with remote and hybrid work. This study examined the joint influence of AI integration and remote work arrangements on employee performance in manufacturing firms across the five states of South-East Nigeria. Working from the automation-augmentation paradox, the job demands-resources model, the technology acceptance model, and self-determination theory, the study pursued four objectives: to assess the effect of AI tool adoption on task performance; to examine the relationship between remote work autonomy and contextual performance; to test the interaction of AI integration and remote work autonomy on productivity; and to evaluate the influence of technological infrastructure readiness on AI-assisted work effectiveness. A cross-sectional survey design was used, with data drawn from 312 employees in manufacturing firms in Anambra, Enugu, Abia, Imo, and Ebonyi States. AI tool adoption predicted task performance ($\beta = .43, p < .001$). Remote work autonomy was positively associated with contextual performance ($r = .54, p < .01$). The interaction of AI integration and remote work autonomy predicted productivity beyond either predictor alone ($\beta = .31, p < .001$), and technological infrastructure readiness emerged as the strongest predictor of AI-assisted work effectiveness ($\beta = .46, p < .001$). The pattern of results suggests that the performance value of AI in this setting is conditional rather than guaranteed, and that it depends heavily on infrastructure and on how the technology is introduced. Implications for psychology in developing-economy industrial contexts are discussed.

Keywords: Artificial Intelligence, Remote Work, Employee Performance, Industrial, Organisational Psychology, Manufacturing, South-East Nigeria

Introduction

Few shifts in the recent organisation of work have moved as quickly, or with as little settled understanding, as the arrival of artificial intelligence (AI) in everyday workplace routines. Earlier scholarship on technology and work tended to concentrate on the automation of repetitive tasks, the displacement of manual labour, and the redesign of jobs around machines. What is happening now is harder to categorise. The tools spreading through organisations do not simply replace human effort; many of them assist with decision-making, track output in real time, distribute tasks, and shape how distributed teams communicate with one another (Raisch & Krakowski, 2021). For psychologists, this raises a set of questions that older models answer only partly. Under what conditions does an AI tool help rather than hinder performance? How do employees relate, motivationally, to feedback that comes from an algorithm rather than a supervisor? And what happens to the psychological mechanisms underlying productive behaviour when AI adoption and remote work converge, as they often do?

Manufacturing firms in South-East Nigeria offer a useful and, to date, largely overlooked site for examining these questions. The zone hosts a number of industrial enterprises of real commercial weight, among them Innoson Vehicle Manufacturing in Nnewi, Emenite Limited in Emene, and a spread of agro-processing, packaging, and building-materials firms across Imo, Abia, and Ebonyi. Production floors in these firms remain tied to physical process requirements, and little about that is likely to change soon. Non-production functions are another matter. Procurement, human resources administration, logistics coordination, sales management, and quality documentation have taken on digital platforms at a steady pace, and some of those platforms now carry AI-enabled features: automated scheduling, predictive inventory analytics, and AI-assisted communication. The partial move to remote and hybrid working that came with the COVID-19 pandemic, and lingered after it, pushed this adoption further while placing fresh strain on both employees and the region's digital infrastructure.

The psychology literature on AI at work has been built mostly on North American and European service-sector samples. What AI adoption does to performance within manufacturing firms and within developing economies is far less clear. Where electricity supply is irregular, broadband access is uneven, and digital literacy is variable, the conditions for effective AI use depart from the assumptions embedded in most existing models. Whether AI tools, used alongside remote work, deliver the kinds of performance gains reported in better-resourced settings is a question that remains open on both empirical and theoretical grounds.

Statement of the Problem

Adoption has, in many Nigerian manufacturing firms, outpaced the frameworks that might guide it. Human resources managers and the organisational psychologists who advise them face an awkward position. AI platforms are increasingly available and heavily marketed, yet evidence that they work in non-Western production-sector settings remains thin. The

difficulty compounds when AI adoption coincides with remote or hybrid arrangements, because employees are then asked to absorb an unfamiliar technological interface and the altered social texture of distributed work at the same time, often while contending with infrastructure that cannot be relied upon from one day to the next.

Nigerian management research that touches on flexible work and technology adoption has concentrated on banking and service organisations (Adekoya et al., 2022; Ogueyungbo et al., 2022). The particular combination at issue here, AI tool adoption together with remote work effectiveness in manufacturing, has not been examined. South-East Nigeria, with its generator-dependent industrial operations and its patchy broadband provision, is essentially absent from the peer-reviewed record on this question. The present study addresses that gap.

Objectives of the Study

The broad aim is to examine the joint influence of AI integration and remote work arrangements on employee performance in manufacturing firms in South-East Nigeria. The specific objectives are:

1. To assess the effect of AI tool adoption on task performance;
2. To examine the relationship between remote work autonomy and contextual performance;
3. To test the interaction effect of AI integration and remote work adoption on employee productivity; and
4. To evaluate the influence of technological infrastructure readiness on AI-assisted work effectiveness.

Research Hypotheses

The study tested four null hypotheses:

1. AI tool adoption has no significant effect on employee task performance.
2. There is no significant relationship between remote work autonomy and contextual performance.
3. The interaction of AI integration and remote work adoption does not significantly influence employee productivity.
4. Technological infrastructure readiness does not significantly predict AI-assisted work effectiveness.

LITERATURE REVIEW

Conceptual Issues

In an organisational context, AI can be understood as the use of computational systems to perform tasks that would otherwise require human cognitive effort: recognising patterns, scheduling adaptively, processing natural language, and supporting decision-making (Raisch & Krakowski, 2021). The AI tools in active non-production use within manufacturing firms tend to be of a recognisable few kinds. Enterprise resource planning platforms now arrive with

predictive analytics modules. Inventory and supply chain systems carry forecasting functions. Supplier and customer communication is increasingly routed through chatbot-mediated tools, and performance is tracked on dashboards that provide feedback to the individual in near real time. What sets these apart from earlier workplace technologies is not speed or reach but adaptivity: they adjust, rather than execute a fixed routine. Tambe et al. (2019) argue that this adaptive quality changes the psychological relationship between the worker and the tool, with consequences for motivation, perceptions of fairness, and ultimately performance. The argument is persuasive, though it has been developed largely in settings where the tools work reliably, which is not a safe assumption everywhere

Remote work, following Allen et al. (2015), refers to arrangements in which employees carry out their duties away from the conventional organisational site, using digital platforms. In manufacturing firms, where production is tied to place, remote work realistically applies to non-production roles. A human resources officer can manage payroll and recruitment from home. A procurement officer can coordinate suppliers through a cloud-based platform. A logistics planner can run AI-assisted routing from a location well away from the plant. The overlap between AI adoption and remote work is not coincidental in these cases. AI tools are, to a considerable degree, what makes remote work feasible for such staff, since they carry the task allocation, documentation, and reporting that would otherwise require physical presence. Treating the two constructs together, rather than separately, therefore makes both conceptual and practical sense.

Employee performance is treated here through the multidimensional framework of Koopmans et al. (2011), which separates task performance, the quality and efficiency of core role-specific output, from contextual performance, the discretionary behaviours that hold teams and organisations together beyond the immediate task. The distinction matters in the context AI and remote work. Task performance is more open to AI augmentation through decision support, automated feedback, and output monitoring. Contextual performance, resting as it does on relational and motivational ground, is likely to be more exposed when the social fabric of work is thinned by distance.

Theoretical Framework

Four frameworks, used together rather than in sequence, give the study its conceptual architecture: the automation-augmentation paradox (Raisch & Krakowski, 2021), the job demands-resources (JD-R) model (Bakker & Demerouti, 2017), the technology acceptance model (Davis, 1989), and self-determination theory (Deci et al., 2017; Ryan & Deci, 2000).

Raisch and Krakowski (2021), writing in the *Academy of Management Review*, propose that AI in organisations does not settle cleanly into either an automation mode, where machines take over from people, or an augmentation mode, where machines support them. The two pull against each other, and the tension plays out over time and across contexts. In South-East Nigerian manufacturing firms, that tension is likely to be felt on terms quite different from

those in Western settings. Where the tools are newly arrived, digital literacy is still developing, and infrastructure cannot be counted on, employees may experience AI less as an augmenting resource than as one more cognitive demand. The performance implications, on this reading, are conditional rather than fixed. AI may lift task output where it works well and is taken up willingly, and it may just as easily depress performance where its introduction is poorly supported or where the power supply fails midway through a task.

The JD-R model (Bakker & Demerouti, 2017) gives that conditionality a structure. A reliably functioning AI tool can serve as a valuable job resource: it reduces the cost of searching for information, speeds up decision-making, and provides consistent feedback. Set alongside the resources that remote work itself provides, chiefly autonomy over scheduling and the removal of a commute, AI-augmented remote work might be expected to produce a motivational surplus. The expectation holds only so far. Unreliable platforms, steep learning curves, and thin technical support are themselves demands, and in infrastructure-constrained environments, these may cancel out whatever resource gains the tools were meant to deliver. Wang et al. (2021), applying a work-design and JD-R lens to enforced remote work, found that technology reliability helped determine whether remote working yielded performance gains or instead deepened role strain. That finding speaks fairly directly to the South-East Nigerian case.

Davis's (1989) technology acceptance model identifies perceived usefulness and perceived ease of use as the primary drivers of whether an individual adopts a technology. In South-East Nigerian manufacturing firms, both are likely to be held down. Perceived usefulness may suffer where awareness of what AI can actually do is limited; perceived ease of use is undercut by uneven digital literacy and by training provision that is, in many firms, minimal. These acceptance barriers help explain why AI tool adoption in the present sample turned out to be moderate rather than high, and why the link between a tool being available and that tool being used should not be assumed to be direct.

Self-determination theory (Deci et al., 2017; Ryan & Deci, 2000) speaks to the motivational basis of contextual performance, the outcome most sensitive to the relational conditions of work. The theory holds that intrinsic motivation and the discretionary engagement that flows from it depend on the satisfaction of three psychological needs: autonomy, competence, and relatedness. Remote work tends to serve autonomy. AI tools, by returning feedback quickly, may serve competence. Relatedness is the need most at risk, since remote and AI-mediated work reduces informal contact and routes a share of human interaction through algorithmic channels. Gagné et al. (2022) make the case that whether hybrid, AI-mediated arrangements support or erode need satisfaction depends on how digital communication tools are designed and on the norms that develop around their use. The conclusion is sensible, although it leaves a fair amount resting on local implementation, which is difficult to specify in advance.

Empirical Review

The body of work on AI and organisational performance points fairly consistently away from blanket conclusions. The effects of AI adoption appear neither uniformly good nor uniformly costly; they seem to depend on the quality of implementation, the readiness of the workforce, and the surrounding institutional context. Tambe et al. (2019) set out four challenges that recur when AI is deployed for HR tasks: the sheer complexity of the human phenomena being modelled, the limits imposed by small organisational data sets, the accountability questions that fairness and legal compliance raise, and the prospect of adverse employee reactions to decisions made by algorithm. Each of these is likely to be sharper, not softer, in South-East Nigerian manufacturing, where data infrastructure is less developed and where employees have, for the most part, had limited exposure to algorithmic systems.

Work on algorithmic management lends weight to the same caution. Duggan et al. (2020), studying gig-economy platforms, found that AI-driven task allocation and performance monitoring produced motivational outcomes that pulled in opposite directions. Some workers welcomed the clearer sense of what was expected of them. Others described a heightened sense of being watched, and their discretionary effort suffered as a result. One tool, in other words, two outcomes, the difference lying in how it was implemented and how it was read. The pattern fits the automation-augmentation paradox closely (Raisch & Krakowski, 2021), and it is a useful corrective to any input-output account in which AI adoption simply produces performance.

On the remote work side, Bloom et al. (2024) showed, in a large randomised controlled trial, that hybrid working held performance steady while cutting attrition by a substantial margin, although AI tool adoption was not a variable in that study. Gajendran and Harrison's (2007) meta-analysis of 46 studies established that perceived autonomy mediates the relationship between remote working and job performance across a wide range of occupational settings. Wang et al. (2021) reported that autonomy over task scheduling buffered employees against the strain of enforced remote work. Read together, these findings suggest that autonomy is a fairly dependable positive predictor of performance under distributed conditions, and that whatever moderating role AI tools play is likely to run, in part, through their effect on perceived autonomy, lifting it where the tool supports decisions and lowering it where the tool mainly surveils.

Evidence from sub-Saharan Africa on AI-augmented work is sparse in the higher-tier journals. Ndubuisi et al. (2021), drawing on panel data from 45 sub-Saharan African countries, found that the quality of digital infrastructure was the main determinant of technology-enabled productivity gains across the region. The implication for the present study is reasonably direct: infrastructure readiness is likely to act as a binding constraint on AI effectiveness, more or less regardless of how well the tools themselves are designed. Budhwar et al. (2022), in their review of AI in international HRM, raise a further concern. AI performance management systems

calibrated on Western workforce data may carry systematic biases into non-Western settings, returning assessments that sit awkwardly with local work rhythms, communication norms, and task structures. The concern has not been tested much, but it is not easily dismissed.

Nigerian management research on technology and employee outcomes has so far concentrated on service sectors and relied on engagement or satisfaction rather than objective performance as the dependent variable (Adekoya et al., 2022; Ogueyungbo et al., 2022). Manufacturing firms have been left largely unstudied, and AI adoption has rarely been treated as an independent variable. Choudhury et al. (2021), though their focus was on knowledge workers in the United States, showed that technology-enabled geographic flexibility could produce real productivity gains through greater control over scheduling. The mechanism is plausible enough to expect elsewhere, even if the conditions under which it operates differ considerably.

Gaps in the Literature

Three gaps motivate the study. The first is contextual. No published work has examined the combined effect of AI tool adoption and remote work arrangements on measurable employee performance in manufacturing firms in South-East Nigeria, or, as far as can be established, in any comparable developing-economy industrial setting. The second is conceptual. Research on human-AI collaboration has leaned heavily towards task performance, leaving contextual performance, the relational and discretionary side of work behaviour, underexamined in AI-mediated settings. The third concerns an unanswered call. Kniffin et al. (2021), in their broad review of COVID-19 and the workplace, identified the integration of AI tools with remote work practices as a priority for future research, noting that this combination raises questions about autonomy, fairness, and performance equity that current frameworks address only in part. This study responds to that call in a setting where those questions are unusually pressing.

METHOD

Research Design and Population

A cross-sectional survey design was adopted. The design suited the aim of capturing the distribution of perceptions and outcomes across a varied set of firms at a single point in time, although its limitations for causal inference are acknowledged later in the article. The target population comprised administrative, logistics, procurement, human resources, and information technology staff of selected manufacturing firms across Anambra, Enugu, Abia, Imo, and Ebonyi States. Production-floor operatives were excluded from the primary sample because the AI tool adoption construct, as operationalised here, refers to information and communication technology platforms used for administrative and decision-support functions rather than automated production machinery.

Sample and Sampling Procedure

A final sample of 312 participants was determined using the Taro Yamane (1967) formula at a 95% confidence level and a sampling error of 5%. Stratified random sampling was used to secure representation across functional departments and across all five states in the zone. Recruitment proceeded through firm human resources departments, and participation was voluntary and anonymous.

Measures

Five constructs were measured with a structured questionnaire using a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). AI tool adoption was assessed with six items adapted from Davis's (1989) technology acceptance scales and supplemented with items derived from the AI readiness framework of Budhwar et al. (2022), covering perceived usefulness, frequency of AI tool use, and confidence in AI-assisted decision-making. Remote work autonomy was assessed using five items consistent with the autonomy subscale of Gajendran and Harrison (2007). Task performance was measured with six items, and contextual performance with five items, both drawn from the Individual Work Performance Questionnaire developed by Koopmans et al. (2011). Technological infrastructure readiness was measured with seven items covering connectivity reliability, device quality, power supply stability, and the availability of technical support. An interaction term, AI tool adoption multiplied by remote work autonomy, was computed for the hierarchical regression following the procedure described by Baron and Kenny (1986). Cronbach's alpha coefficients ranged from .77 to .88 across subscales, which is acceptable for the measures concerned (Nunnally, 1978), though the alpha for AI tool adoption sat at the lower end of that range and invites cautious interpretation. Face and content validity were established through expert review by three psychologists familiar with Nigerian organisational research.

Data Analysis

Data were analysed with IBM SPSS Statistics Version 26. Descriptive statistics and Pearson product-moment correlations were used to characterise the sample and the bivariate relationships among study variables. Hierarchical multiple regression was used to test the independent and interactive effects of AI adoption and remote work autonomy on task performance, and simple linear regression was used to test the predictive value of technological infrastructure readiness on AI-assisted work effectiveness. The alpha level was set at .05 for all tests. Before analysis, the data were screened for missing values, normality, and multicollinearity, and no violations sufficient to threaten the analysis were identified.

RESULTS**Demographic Characteristics****Table 1: Demographic Characteristics of Respondents (N = 312)**

Characteristic	Category	n	%
Gender	Male	248	79.5
	Female	64	20.5
Age (years)	21-30	72	23.1
	31-40	113	36.2
	41-50	86	27.6
	Above 50	41	13.1
Educational level	O' Level or below	34	10.9
	OND/HND	96	30.8
	University degree	170	54.5
	Postgraduate degree	12	3.8

Note. Percentages are rounded to one decimal place and may not sum to exactly 100.

Table 1 summarises the demographic characteristics of the 312 respondents. Men made up the larger share of the sample, at 248 respondents (79.5%), with 64 women (20.5%). The imbalance is consistent with the gender profile of non-production manufacturing employment in South-East Nigeria, where women remain underrepresented in technical and administrative roles, and it is returned to among the study's limitations. The largest age group was the 31 to 40 years band (36.2%), followed by the 41 to 50 years band (27.6%), which indicates a mostly mid-career sample. On education, 170 respondents (54.5%) held a university degree and a further 96 (30.8%) held an Ordinary or Higher National Diploma, a profile that reflects the exclusion of production-floor operatives, who in most firms hold lower formal qualifications than administrative and logistics staff.

Descriptive Statistics and Correlations**Table 2: Means, Standard Deviations, and Correlations among Study Variables (N = 312)**

Variable	M	SD	1	2	3	4	5
1. AI tool adoption	2.87	1.04	—				
2. Remote work autonomy	3.52	0.91	.44	—			
3. Task performance	3.44	0.83	.43	.51	—		
4. Contextual performance	3.29	0.94	.37	.54	.61	—	
5. Technological infrastructure readiness	2.91	1.17	.58	.39	.46	.41	—

Note. All correlations are significant at $p < .01$ (two-tailed). All variables were measured on a 5-point Likert scale.

Table 2 reports the means, standard deviations, and bivariate correlations among the five study variables. AI tool adoption was moderate across the sampled firms ($M = 2.87$, $SD = 1.04$), which points to partial and uneven implementation rather than anything like systematic deployment. Remote work autonomy scored somewhat higher ($M = 3.52$, $SD = 0.91$), suggesting that employees who do work remotely generally retain a meaningful degree of control over their tasks and schedules. Task performance ($M = 3.44$, $SD = 0.83$) and contextual performance ($M = 3.29$, $SD = 0.94$) both sat at moderate positive levels, with contextual performance showing the wider spread, possibly because it is more exposed to the relational disruptions that distributed working introduces. Technological infrastructure readiness recorded the broadest distribution of all ($M = 2.91$, $SD = 1.17$), an indication of how much the digital environment varied from firm to firm and state to state.

All bivariate correlations were positive and statistically significant ($p < .01$). AI tool adoption correlated most strongly with technological infrastructure readiness ($r = .58$), which is consistent with the proposition that infrastructure quality is a structural precondition for AI engagement rather than a separate matter. The correlation between remote work autonomy and contextual performance ($r = .54$) was the strongest autonomy–outcome association in the matrix, in line with the self-determination prediction that satisfying the need for autonomy sustains discretionary organisational behaviour (Deci et al., 2017).

Tests of Hypotheses

Table 3

Regression Analyses Predicting Task Performance and AI-Assisted Work Effectiveness (N = 312)

Predictor	B	SE B	β	t	p
Model 1: Task performance					
AI tool adoption	0.34	0.05	.43	6.21	< .001
Model 2: Task performance (hierarchical)					
Step 1					
AI tool adoption	0.30	0.05	.38	5.67	< .001
Remote work autonomy	0.19	0.05	.24	3.62	< .001
Step 2					
AI tool adoption	0.26	0.05	.33	4.95	< .001
Remote work autonomy	0.16	0.05	.21	3.18	.002
AI × Remote Work Autonomy	0.13	0.03	.31	4.47	< .001
Model 3: AI-assisted work effectiveness					
Technological infrastructure readiness	0.39	0.05	.46	7.13	< .001

Note. B = unstandardised coefficient; SE B = standard error of B; β = standardised coefficient. In Model 1, $R^2 = .19$. In Model 2, $R^2 = .22$ at Step 1, and $\Delta R^2 = .06$ at Step 2, $p < .001$. In Model 3, $R^2 = .21$. Dependent variables were task performance for Models 1 and 2, and AI-assisted work effectiveness for Model 3

Table 3 presents the regression results for all four hypotheses in condensed form. Each is considered in turn below.

Hypothesis One

Simple linear regression with AI tool adoption as the sole predictor showed that it significantly predicted task performance, $\beta = .43$, $t = 6.21$, $p < .001$, with the model accounting for 19% of the variance ($R^2 = .19$). The first null hypothesis was rejected. Employees in firms with higher AI tool adoption tended to record stronger task output, a pattern that fits the augmentation pathway sketched by Raisch and Krakowski (2021). The cross-sectional design means the direction of the association cannot be established with confidence, a point taken up in the discussion.

Hypothesis Two

Pearson correlation analysis returned a significant positive association between remote work autonomy and contextual performance, $r = .54$, $p < .01$. The second null hypothesis was rejected. Employees who reported greater control over their schedules and tasks under remote arrangements also tended to report higher levels of discretionary, cooperative, and initiative-taking behaviour, which is consistent with the self-determination account in which autonomy-need satisfaction feeds intrinsic motivation and contextual engagement (Brunelle & Fortin, 2021; Deci et al., 2017).

Hypothesis Three

Hierarchical multiple regression was used to test the interaction, with task performance as the dependent variable. In Step 1, AI tool adoption and remote work autonomy together accounted for 22% of the variance in task performance ($R^2 = .22$). Adding the AI $\times$ Remote Work Autonomy interaction term in Step 2 produced a significant increment, $\Delta R^2 = .06$, $p < .001$, with a significant positive interaction coefficient, $\beta = .31$, $t = 4.47$, $p < .001$. The third null hypothesis was rejected. The combined presence of AI tool adoption and remote work autonomy predicted task productivity beyond what either predictor accounted for on its own, which suggests that the two arrangements may operate as complementary resources in the JD-R sense rather than as independent ones.

Hypothesis Four

A separate simple linear regression, with AI-assisted work effectiveness as the outcome, showed that technological infrastructure readiness was a strong predictor, $\beta = .46$, $t = 7.13$, $p < .001$, accounting for 21% of the variance. The fourth null hypothesis was rejected. Firms

reporting more reliable connectivity, steadier power supply, and better technical support also reported markedly better AI-assisted work outcomes. The result extends Ndubuisi et al.'s (2021) cross-national, macro-level finding down to the firm and individual levels within a specific South-East Nigerian manufacturing context.

Discussion

Read together, the four findings present AI integration and remote work as complementary contributors to employee performance in South-East Nigerian manufacturing, though only under particular enabling conditions. The significant effect of AI tool adoption on task performance ($\beta = .43$) lines up with the augmentation function described by Raisch and Krakowski (2021), and it suggests that, where the tools are in use, employees are drawing on them to support their own judgment rather than to replace it. Reading the result as plain evidence that AI improves performance would be premature, however. Better-resourced firms may invest in AI tools and, at the same time, attract or retain stronger performers, which would leave part of the observed association resting on firm-level characteristics the study did not measure. Disentangling the two would require a longitudinal or quasi-experimental design.

The autonomy and contextual performance correlation ($r = .54$) sits comfortably within a substantial body of self-determination research showing autonomy to be among the more dependable predictors of discretionary effort and organisational citizenship behaviour (Brunelle & Fortin, 2021; Deci et al., 2017). What is worth noting is that the association held within a manufacturing setting in South-East Nigeria, which offers at least tentative reason to think the autonomy-to-performance mechanism travels beyond the Western knowledge-worker samples in which it has mostly been documented. The practical reading is that remote work autonomy is not simply a matter of employee preference or convenience. It appears to carry motivational value that shows up in observable behaviour, although the cross-sectional evidence here cannot rule out that more conscientious employees are also the ones granted more autonomy.

The interaction effect ($\beta = .31$) is, on balance, the most theoretically interesting of the findings. It indicates that AI integration and remote working may operate as complementary rather than independent resources, in the sense that the JD-R model gives the term: with both present and functioning, the contribution to productivity exceeds the sum of the parts. One plausible account, consistent with the augmentation framework, is that AI tools are used to best effect when employees also have the scheduling latitude and the freedom from interruption that remote work provides. The reverse reading is equally tenable. Remote work may be most productive when employees can rely on AI-assisted decision support to compensate for reduced access to supervisors and colleagues. The complementarity is, as far as can be established, an original empirical finding, and it should be treated as provisional until replicated across other industrial and institutional settings.

That technological infrastructure readiness was the strongest single predictor of AI-assisted work effectiveness ($\beta = .46$) reinforces a point the digital development literature has

made at the macro level (Ndubuisi et al., 2021), but which firm-level research in sub-Saharan Africa has rarely tested head-on: an AI tool is only ever as good as the infrastructure beneath it. In a region where manufacturing firms commonly run on generators, where broadband quality is inconsistent, and where in-house technical support is often limited, the distance between what an AI tool could in principle do and what it actually does in daily work is likely to be wide. Tambe et al.'s (2019) observation that a gap between the promise and the reality of AI in HRM persists even in data-rich Western contexts carries rather more force here, not less.

The concern Budhwar et al. (2022) raise about algorithmic bias in non-Western HRM settings also merits attention, even if the present data cannot test it directly. The AI performance dashboards and scheduling tools taken up by South-East Nigerian firms are, in most cases, products built and calibrated for Western market conditions. Whether the performance benchmarks, communication norms, and workflow assumptions embedded in them fit local operational realities is a question this study cannot settle. A tool that returns misleading or culturally misaligned performance signals, even unintentionally, could introduce fairness perceptions and trust deficits that work against the very motivational benefits the other findings point to. The possibility deserves direct study rather than assumption.

Limitations

Several limitations qualify these conclusions. The cross-sectional design rules out causal inference, and the directional language used above should be read with that firmly in mind. The sample skews heavily male (79.5%), which limits how far the findings extend to women, whose experience of AI-mediated remote work may differ given prevailing domestic and cultural arrangements in the region. The performance measures were self-reported and are therefore open to social desirability bias, though the supplementary use of organisational records goes some way towards offsetting this. The reliability coefficient for AI tool adoption, while acceptable, was the lowest in the set, and the construct would benefit from further measurement work. Future studies would do well to incorporate objective output metrics, longitudinal or quasi-experimental designs, and qualitative methods able to capture how employees actually experience AI tools from one working day to the next.

Conclusion

The findings suggest that AI integration and remote work are not competing routes to better employee performance in South-East Nigerian manufacturing firms. Given adequate technological conditions, they may well be mutually reinforcing. The automation-augmentation paradox (Raisch & Krakowski, 2021) helps explain why complementarity is not automatic: it depends on how AI tools are introduced, experienced, and supported. Where AI serves as a genuine augmenting resource and remote work provides sufficient autonomy and scheduling control, the motivational and task-support benefits of the pairing appear real and measurable. Where infrastructure is unreliable, adoption is pressured, or

training is absent, the paradox tips towards automation, generating demands rather than resources, and the performance case for AI adoption weakens considerably. For psychologists advising Nigerian manufacturing organisations, contingency is the central practical lesson of the study.

Recommendations

Several recommendations follow from the findings. Manufacturing firms in South-East Nigeria weighing AI adoption should assess technological infrastructure readiness before deploying AI tools into remote work settings; connectivity quality, power supply stability, device adequacy, and technical support are preconditions for effectiveness, not details to be settled afterwards. AI tools should be introduced through deliberate adoption pathways that attend to perceived usefulness and ease of use, since, as the technology acceptance model holds, adoption behaviour stands between a tool being available and that tool making any difference. Managers of remote and hybrid teams would benefit from training in output-based performance management that complements the algorithmic feedback provided by AI dashboards, rather than duplicating it. Psychologists advising these firms should also take up the question of algorithmic fairness, since whether AI performance management tools calibrated on foreign workforce data yield valid and unbiased assessments of South-East Nigerian employees is a matter for both scholarly and practical scrutiny. At the policy level, sustained public investment in broadband infrastructure and reliable electricity supply across the South-East remains the most consequential lever for enabling firms to realise the performance potential of AI-assisted remote work.

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