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Algorithmic Management and the Future of Work in Organisations: A Theoretical Account of Control, Autonomy and Skill Formation Under AI-Mediated Supervision

OGAH Sunday Ogbo[1], IGWE Emmanuel Sunday[2], NWOGBOJI Emmanuel Usulor[3]

[1,2,3] Veristzon Global Research Lab

ABSTRACT

Algorithmic management, the use of software and artificial intelligence (AI) to assign, monitor, evaluate and discipline work, has spread from platform labour into conventional organisations through productivity analytics, AI-assisted scheduling, automated performance scoring and generative AI assistants. Existing research treats algorithmic management largely as a single construct, concentrates on autonomy and well-being in the present, and pays little attention either to the long-run formation of expertise or to African labour markets. This study develops a theoretical account of what changes when supervision is mediated by algorithms. It adopts a conceptual, theory-building design based on an integrative review of thirty peer-reviewed journal articles published between 2023 and 2026, identified through keyword searches and citation chaining, screened against explicit inclusion criteria, verified against publisher records and checked for retractions and corrections. The articles were coded deductively against organisational control theory and inductively for outcomes and moderating conditions, drawing also on self-determination theory and theories of expertise and cognitive offloading. The analysis distinguishes three supervisory functions that algorithms take over (direction, evaluation and discipline) and shows that each affects employee autonomy, trust in managers and skill formation differently. It identifies a skill-formation paradox: the step-by-step algorithmic guidance that raises short-run productivity, particularly for novice workers, suppresses the effortful practice through which tacit expertise is built, so that organisations may trade future capability for present output. Eight testable propositions are derived, together with measures for each construct, and labour-market slack, informality and weak enforcement of data protection are specified as conditions that intensify these effects in African economies. The paper recommends that organisations decide separately whether to automate each function and avoid automating discipline by default, design guidance that fades as competence grows, explain performance scores to workers, and keep a named human responsible for sanctions with a route of appeal. Regulators are urged to translate data-protection provisions into enforceable workplace rights to explanation and human review.

Keywords: algorithmic management; future of work; human resource management; employee autonomy; organisational control

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1. INTRODUCTION

Supervision is one of the oldest functions of management, and for most of its history it has been carried out by people. A supervisor assigns work, watches how it is done, judges the result and acts on that judgement. Over the past decade a growing share of this activity has been handed to software. Ride-hailing and delivery platforms were the first to show that a workforce of millions could be directed, rated and disciplined almost entirely by algorithms, and the term *algorithmic management* was coined to describe that arrangement (Kadolkar et al., 2025; Keegan & Meijerink, 2025). What has changed since 2023 is that the same logic has moved into conventional organisations. Warehouses, retail chains, banks, contact centres, hospitals and professional-service firms now use productivity analytics, AI-assisted scheduling, automated performance scoring and, increasingly, generative AI assistants that tell employees what to do next (Keegan & Meijerink, 2025; Kinowska & Sienkiewicz, 2023; Noponen et al., 2024). Algorithmic management is no longer a feature of the gig economy at the edge of the labour market; it is becoming an ordinary part of how work is supervised.

The consequences matter for managers and for workers. Supporters point to consistency, speed and productivity gains, and the field experiments on AI assistance show that these gains are real, particularly for less experienced workers (Brynjolfsson et al., 2025; Noy & Zhang, 2023). Critics point to intensified surveillance, loss of discretion and the erosion of the relationship between employees and their managers (Noponen et al., 2024; Ravid et al., 2023; Röttgen et al., 2025). Both positions are supported by evidence, which suggests that the question is less whether algorithmic management is good or bad than which parts of supervision are automated, under what conditions, and with what effects over time.

Three gaps limit the current literature. First, algorithmic management is usually treated as a single construct, even though the functions it absorbs (deciding what work is done and how, judging performance, and applying rewards and sanctions) have different effects on the people being managed. Recent reviews call for finer-grained theory, but the field still lacks an account that links each function to distinct outcomes (Kadolkar et al., 2025; Meijerink & Bondarouk, 2023; Noponen et al., 2024). Second, research has concentrated on autonomy, well-being and fairness in the present, and has paid little attention to what happens to expertise over time. A separate body of work in cognitive psychology, information systems and medicine shows that AI assistance can accelerate skill decay and inhibit skill development, often without the worker noticing (Budzyń et al., 2025; Macnamara et al., 2024; Rinta-Kahila et al., 2023). These two literatures have not been connected, so organisations lack a framework for anticipating how algorithmic supervision shapes the formation of the tacit skills on which they later depend. Third, most of the evidence comes from North America, Europe and China. African economies, where platform work is expanding quickly, informal employment is widespread and labour-market and data-protection institutions differ, are under-represented, and the conditions that moderate the effects of algorithmic management there are under-theorised (Adekoya et al., 2025; Dinika, 2025; Ekdale & Aidoo, 2024).

This paper addresses these gaps. Its purpose is to develop a theoretical account of what changes when supervision is mediated by algorithms. Specifically, it seeks to answer three research questions:

RQ1: Which distinct supervisory functions do algorithmic systems take over, and how does each affect employee autonomy and trust in managers?

RQ2: How does algorithmic supervision affect the formation of employee skill and expertise, and does a trade-off exist between short-run productivity and long-run capability?

RQ3: What design principles and institutional conditions can preserve autonomy and learning under algorithmic management, with particular reference to African economies?

Section 2 reviews the literature, Section 3 sets out the method, Section 4 presents and discusses the framework, and Sections 5 and 6 conclude.

2. LITERATURE REVIEW

2.1 Conceptual Review

2.1.1 Algorithmic management and AI-mediated supervision

Algorithmic management refers to the use of software, data and algorithms to carry out functions that were traditionally performed by human managers, including allocating and scheduling work, setting goals, monitoring behaviour, rating performance and determining pay or

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continued access to work (Kadolkar et al., 2025; Parent-Rocheleau et al., 2024). The concept originated in studies of ride-hailing and delivery platforms, but recent reviews show that it now describes practices inside conventional organisations as well, where human resource management (HRM) systems, workforce analytics and AI tools take over parts of the supervisory role (Keegan & Meijerink, 2025; Noponen et al., 2024). In this paper, *AI-mediated supervision* denotes the broader situation in which a worker's day-to-day direction, evaluation or discipline is delivered or substantially shaped by an algorithm, whether or not a human manager remains formally responsible. This framing deliberately includes generative AI assistants that prescribe the next step in a task, because such systems perform the directing function even when they are introduced as productivity tools rather than as management systems (Anthony et al., 2023; Brynjolfsson et al., 2025).

2.1.2 Employee autonomy

Job autonomy is the degree of discretion a worker has over the methods, sequence, timing and criteria of their work. It is a core resource in work-design research and a basic psychological need in self-determination theory. Algorithmic management bears directly on it because the functions it automates are precisely those through which discretion is granted or withdrawn (Meijerink & Bondarouk, 2023; Röttgen et al., 2024).

2.1.3 Skill formation and cognitive offloading

Skill formation is the process through which workers acquire and maintain the explicit and tacit knowledge needed to perform, adapt and exercise judgement. It depends on effortful practice, feedback on errors and opportunities to solve problems without full guidance. *Cognitive offloading* is the use of external aids to reduce the mental effort required by a task. Offloading can improve immediate performance, but when an AI system performs the reasoning, the practice through which skill is built and maintained may be lost (Gerlich, 2025; Macnamara et al., 2024). *Skill erosion* refers to the resulting decline of previously held competence, and *deskilling* to the wider reduction of the skill content of work (Rinta-Kahila et al., 2023).

2.2 Theoretical Review

2.2.1 Organisational control theory

Control theory treats management as the set of mechanisms through which organisations align worker behaviour with organisational goals. Classical accounts distinguish direction (specifying what is to be done), evaluation (monitoring and assessing performance) and discipline (rewarding or sanctioning). Algorithmic control can be read as an intensification of technical control: the rules are embedded in the technology and the supervisor's discretion is replaced by code. Recent work shows that this reading is incomplete. Algorithmic control can be experienced as guiding as well as restrictive, and drivers' judgements of its legitimacy depend on how it affects their autonomy, fairness and privacy (Wiener et al., 2023). Cameron (2024) shows that algorithmic management can also manufacture consent: by breaking work into a constant stream of small, bounded choices, it gives workers a sense of agency and skill that makes the job feel "good" while obscuring its structural costs. Noponen et al. (2024) describe the resulting tension as a choice between "Taylorism on steroids" and enabling autonomy, and conclude that organisations mostly use algorithmic management for control. Control theory therefore provides the decomposition used in this paper, while recent studies show that the effects of each function depend on how it is designed and experienced.

2.2.2 Self-determination theory and work design

Self-determination theory (SDT) holds that motivation and well-being depend on the satisfaction of three basic needs: autonomy, competence and relatedness. Work-design research applies the same logic to job characteristics, treating autonomy, task variety and problem-solving demands as resources that sustain motivation and learning. From this perspective, algorithmic management matters because it changes the design of jobs. Conceptual syntheses predict that it reduces action-regulation resources such as autonomy, transparency and predictability, and lowers intellectual demands such as problem solving (Röttgen et al., 2024). Meijerink and Bondarouk (2023) add that the relationship runs in both directions: HRM algorithms both restrict and enable autonomy, and workers in turn reshape the algorithms through their responses.

2.2.3 Expertise, deliberate practice and cognitive offloading

Theories of expertise hold that skilled performance develops through deliberate practice: repeated, effortful attempts at tasks just beyond current ability, with feedback that allows errors to be detected and corrected. Applied to AI assistance, this implies a trade-off. Assistance that removes errors and effort improves present performance but can deprive learners of practice and allow experts' skills to decay, often without the performer noticing (Macnamara et al., 2024). Rinta-Kahila et al. (2023) model the organisational version of this process as a set of vicious circles in which reliance on automation breeds complacency, which weakens awareness of the work, the maintenance of competence and the checking of outputs, so that skill erodes without anyone noticing.

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2.3 Empirical Review

Table 1 summarises the main empirical studies reviewed. Four bodies of evidence are relevant.

Algorithmic management, autonomy and well-being. Survey evidence consistently links exposure to algorithmic management with lower job autonomy. In the scale-development studies for the Algorithmic Management Questionnaire, overall exposure among 1,332 gig workers was negatively related to job autonomy and job complexity (Parent-Rocheleau et al., 2024), and a German validation study across six samples found that more complete algorithmic management was associated with lower autonomy, higher work pace and greater irritation (Röttgen et al., 2025). Beyond platforms, an analysis of 21,869 European establishments found that algorithmic management affected workplace well-being both directly and indirectly through reduced job autonomy and rewards (Kinowska & Sienkiewicz, 2023). Qualitative studies show how autonomy changes over time: platform experimentation first expanded and then curtailed workers' autonomy before the new arrangement became normalised (Rahman et al., 2023).

Monitoring, transparency and fairness. A meta-analysis of 94 samples found no evidence that electronic performance monitoring improves performance, an association with higher worker stress, and more positive attitudes when monitoring was transparent and less invasive (Ravid et al., 2023). Experiments show that intensive monitoring lowers workers' willingness to accept gig jobs, mainly through privacy concerns, and that transparency helps only when monitoring is light (Liang et al., 2023). The fairness evidence is mixed. Among 962 gig workers, exposure to algorithmic compensation raised time-based stress but was positively related to perceived procedural justice, and perceived transparency strengthened that link (Semujanga & Parent-Rocheleau, 2024). Experimental evidence suggests that employees trust AI more than supervisors for formula-based feedback but prefer humans for discretionary judgements, and respond best to hybrid arrangements (Biswas et al., 2024). Studies of Uber drivers show that opacity makes workplace tensions harder to resolve and forces workers into continuous "algorithm sensemaking" (Möhlmann et al., 2023), that the algorithm acts as co-worker, supervisor and evaluator at once but cannot register the human consequences of its decisions (Tarafdar et al., 2023), and that algorithmic systems often delegate work back to humans in collective and hybrid ways (Stelmaszak et al., 2025).

Productivity and skill under AI assistance. Field and laboratory experiments show sizeable short-run gains from AI assistance. Access to ChatGPT reduced writing-task time by 40% and raised quality by 18% among professionals (Noy & Zhang, 2023), and an AI assistant raised the number of customer issues resolved per hour by about 15% among support agents, with the largest gains for the least experienced (Brynjolfsson et al., 2025). The evidence on skill points the other way. In four Polish endoscopy centres, the adenoma detection rate in standard colonoscopy fell from 28.4% to 22.4% after endoscopists were routinely exposed to AI assistance (Budzyń et al., 2025). In a field experiment with high-school students, unrestricted access to a generative AI tutor improved practice performance but harmed learning once access was removed, whereas a version with pedagogical safeguards largely avoided that harm (Bastani et al., 2025). Survey and review evidence links heavy AI use and over-reliance on AI dialogue systems with weaker critical thinking and analytical reasoning, although these studies are largely cross-sectional (Gerlich, 2025; Zhai et al., 2024). In an accounting firm, reliance on cognitive automation produced skill erosion that remained hidden until the system's limitations were exposed (Rinta-Kahila et al., 2023).

African evidence. Research on algorithmic management in Africa is recent and largely qualitative. In Nigeria, interviews with Uber and Bolt drivers show ultra-precarious conditions under which drivers stay for flexibility and income while relations with the platform become purely transactional (Adekoya et al., 2025). In Nairobi, drivers whose autonomy is tightly constrained by ride-hailing apps resist individually and collectively, drawing on solidarity rooted in Kenya's informal "hustling" culture (Ekdale & Aidoo, 2024). Across Rwanda, South Africa and Zimbabwe, algorithmic management reduces workers' financial, task and behavioural autonomy in ways that echo older patterns of labour exploitation (Dinika, 2025).

Table 1. Summary of key empirical studies reviewed

Study	Setting and method	Key finding
Parent-Rocheleau et al. (2024)	1,332 gig workers; scale development	Algorithmic management exposure negatively related to job autonomy and job complexity
Röttgen et al. (2025)	Six German samples (N = 1,005); survey	Lower autonomy, higher work pace and irritation
Kinowska & Sienkiewicz (2023)	21,869 European establishments; SEM	Well-being affected directly and via reduced autonomy and rewards
Ravid et al. (2023)	Meta-analysis, 94 samples	No performance gain from monitoring; higher stress; transparency helps
Liang et al. (2023)	Online experiments	Intensive monitoring deters gig workers through privacy concerns

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Study	Setting and method	Key finding
Semujanga & Parent-Rocheleau (2024)	962 gig workers; survey	Algorithmic pay raises time stress; transparency strengthens justice perceptions
Noy & Zhang (2023)	453 professionals; experiment	40% less time and 18% higher quality on writing tasks
Brynjolfsson et al. (2025)	5,172 support agents; staggered roll-out	About 15% more issues resolved per hour; largest gains for novices
Budzyń et al. (2025)	Four endoscopy centres; observational	Unassisted detection rate fell from 28.4% to 22.4% after AI exposure
Bastani et al. (2025)	About 1,000 students; field experiment	Unrestricted AI aided practice but harmed later learning; guardrails mitigated harm
Rinta-Kahila et al. (2023)	Accounting firm; case study	Automation reliance produced hidden skill erosion
Adekoya et al. (2025)	49 interviews, Nigeria	Ultra-precarity; transactional platform–driver relations
Ekdale & Aidoo (2024)	30 drivers, Nairobi	Constrained autonomy met by individual and collective resistance
Dinika (2025)	41 workers, Rwanda, South Africa, Zimbabwe	Reduced financial, task and behavioural autonomy

2.4 Gaps in the Literature

The review reveals three gaps. First, algorithmic management is measured and theorised mainly as an overall level of exposure. The functions it absorbs are listed in measurement instruments, but their distinct consequences are rarely theorised (Kadolkar et al., 2025; Parent-Rocheleau et al., 2024). Second, the algorithmic-management literature and the literature on skill under AI assistance have developed separately. The first studies autonomy and well-being in the present; the second shows that assistance can trade future competence for present performance. Neither asks how supervision by algorithms shapes the long-run formation of expertise in organisations. Third, the African evidence documents precarity and resistance but has not yet been connected to general theory about which institutional conditions amplify or soften the effects of algorithmic control. The framework developed in Section 4 addresses these gaps.

3. MATERIALS AND METHODS

3.1 Research Design

The study is a conceptual, theory-building paper based on an integrative literature review. It does not collect primary data. An integrative design was chosen over a systematic review with meta-analysis for two reasons: the relevant evidence is spread across management, information systems, labour studies, cognitive psychology and medicine, which use incompatible outcome measures; and the objective is to build explanatory theory (functions, mechanisms and propositions) rather than to estimate a pooled effect.

3.2 Population of Literature and Search Strategy

The population comprised peer-reviewed journal articles on algorithmic management, electronic performance monitoring, AI-assisted work and skill formation under automation. Searches combined the terms "algorithmic management", "algorithmic control", "electronic performance monitoring", "platform work" or "gig work", "job autonomy", "trust", "deskilling", "skill erosion", "cognitive offloading" and "generative AI" with "productivity", "learning" or "expertise", and, for the contextual analysis, "Africa", "Nigeria", "Kenya", "South Africa" and "Ghana". Searches were run in academic search engines and publisher platforms and supplemented by backward and forward citation chaining from the most-cited reviews retained.

3.3 Inclusion and Exclusion Criteria

Articles were included if they (a) were published in a peer-reviewed journal with a volume or issue year of 2023 to 2026; (b) reported empirical evidence, a systematic review or a theoretical argument directly relevant to direction, evaluation or discipline of work by algorithms, or to skill formation under AI assistance; (c) were written in English; and (d) could be matched to a publisher record giving authors, title, journal, volume, issue, pages or article number and a digital object identifier (DOI). Preprints, working papers, conference proceedings, books, practitioner magazines and sources that could not be verified were excluded. Each retained article was screened for retractions, expressions of concern and corrections on the publisher's page before citation. Thirty journal articles met the criteria and form the evidence base listed in the references.

3.4 Analysis and Bases of Judgement

Retained articles were read in full where access allowed and coded deductively against three a priori categories derived from control theory (direction, evaluation, discipline) and inductively for outcomes (autonomy, trust and fairness, well-being, productivity, skill formation) and for moderating conditions (transparency, voice, labour-market and regulatory context). Relationships that appeared consistently across different settings and methods were elevated to propositions; relationships supported by a single study or by one setting only were treated as boundary conditions or as questions for future research. The propositions were judged against four criteria for theoretical contribution: they must be logically derived from the reviewed evidence, add explanation

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beyond existing accounts, be falsifiable with available measures, and have clear practical implications.

3.5 Reliability and Validity

Because the evidence is secondary, reliability rests on the transparency and reproducibility of the source base. Every citation was checked against its publisher record, so that a reader can retrieve the same sources. Construct validity was protected by defining each construct before coding (Section 2.1) and by tracing each proposition to the specific studies that support it. Threats to validity are acknowledged: the evidence is dominated by platform and Global North settings, several key findings come from a small number of experiments, and the African evidence is largely qualitative.

3.6 Variable Measurement for Future Testing

To make the propositions testable, Table 2 sets out how each construct can be operationalised in survey, field or experimental research.

Table 2. Operationalisation of constructs for empirical testing

Construct	Suggested measurement	Level / source
Algorithmic direction, evaluation, discipline	Algorithmic Management Questionnaire subscales (Parent-Rocheleau et al., 2024; Röttgen et al., 2025); system logs of prompt frequency and granularity	Worker survey; system data
Job autonomy	Established work-design autonomy scales (method, scheduling, decision-making)	Worker survey
Trust and perceived fairness	Trust-in-management and procedural-justice scales; perceived transparency of scoring	Worker survey
Skill formation	Unassisted performance on transfer or "AI-off" tasks compared with assisted performance over time	Field test; experiment
Short-run productivity	Output per hour, resolution rate, error rate while assisted	Administrative data
Long-run capability	Recovery time after system outage; performance on novel tasks; internal promotion readiness	Organisational records
Institutional context	Unemployment and informality rates; existence and enforcement of data-protection law	Secondary national data

3.7 Ethical Considerations and AI Usage Disclosure

The study used only published sources and required no ethical approval. In line with the journal's disclosure requirements, the author(s) declare that a generative AI assistant (Claude, Anthropic) was used to support literature retrieval, metadata checking, structuring and language editing. All arguments, propositions and interpretations were reviewed by the author(s), every cited source was checked against its publisher record, and the author(s) take full responsibility for the content. No data, results or citations were generated by AI.

4. RESULTS AND DISCUSSION

4.1 RESULTS

The synthesis yields three results: a functional decomposition of algorithmic management, a set of eight propositions linking those functions to autonomy, trust and skill formation, and a set of design principles derived from the propositions. Because the study is conceptual, the "results" are theoretical claims built from the reviewed evidence rather than new data; each claim is stated so that it can be tested and, if wrong, rejected.

4.1.1 Result 1: A direction–evaluation–discipline decomposition

Supervision, in the managerial sense, bundles three activities: telling people what to do and how (direction), judging how well they did it (evaluation), and acting on that judgement through rewards, corrections or sanctions (discipline). Algorithmic systems can absorb any one of these without absorbing the others, and organisations increasingly mix them: a warehouse may automate direction through pick-path software while leaving evaluation to supervisors; a contact centre may keep human team leaders but hand evaluation to sentiment and handling-time analytics; a ride-hailing platform automates all three. Table 3 sets out the decomposition. Its value is that each function touches a different part of the employment relationship, so the consequences of "algorithmic management" depend on which function has been automated, how granular it is, and whether a human remains able to override it.

Table 3. The direction–evaluation–discipline decomposition of algorithmic management

Function	What the algorithm takes over	Typical technologies	Primary effect on autonomy and trust	Primary effect on skill formation
Direction	Allocating tasks, sequencing work, prescribing method step by step	Dispatch and scheduling engines; pick-path and route optimisation; AI copilots and next-best-action prompts	Narrows discretion over method, order and pace; trust shifts from the manager to the system's instructions	Strongest: removes the problem-solving and error-correction episodes through which tacit skill is built

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Function	What the algorithm takes over	Typical technologies	Primary effect on autonomy and trust	Primary effect on skill formation
Evaluation	Measuring and scoring performance continuously and comparing workers	Productivity analytics; keystroke and activity monitoring; customer ratings; algorithmic rankings	Felt surveillance and narrowing of effort towards what is measured; opacity weakens perceived fairness	Indirect: feedback becomes frequent but thin, rewarding speed on measured tasks over learning
Discipline	Acting on scores through incentives, nudges, warnings or deactivation	Dynamic pay and bonus rules; automated warnings; account suspension or deactivation	Largest effect on trust and voice: sanctions without a human interlocutor are experienced as arbitrary	Indirect: fear of sanction discourages experimentation and deviation from the script

4.1.2 Result 2: Propositions

The propositions follow the decomposition. They are stated at the level of the work unit and assume that the system is used as designed; their boundary conditions are discussed afterwards.

Direction and autonomy. When an algorithm specifies the sequence and method of each task, the worker's decision space contracts to compliance or override. Self-determination theory predicts that the loss of discretion frustrates the need for autonomy even when the instructions are good, and the platform evidence shows that workers experience step-by-step direction as control rather than help when they cannot see the logic behind it (Möhlmann et al., 2023; Parent-Rocheleau et al., 2024; Röttgen et al., 2025; Tarafdar et al., 2023).

Proposition 1 (P1): The more granular the algorithmic direction of a task (the degree to which method, sequence and pace are prescribed), the lower the job autonomy that workers experience.

Evaluation and autonomy. Continuous measurement changes what work is for. Workers who know that a narrow set of indicators is recorded and ranked reallocate effort towards those indicators, and the meta-analytic evidence on electronic performance monitoring finds no evidence that monitoring improves performance but an association with higher stress (Liang et al., 2023; Ravid et al., 2023).

Proposition 2 (P2): The frequency and granularity of algorithmic evaluation are negatively related to experienced autonomy, an effect transmitted through felt surveillance.

Evaluation, discipline and trust. Trust in a supervisor rests on the belief that judgements are competent, fair and open to explanation. Opaque scores and automated sanctions weaken all three: the worker cannot see how the judgement was reached, cannot contest it with a person, and may conclude that the manager has abdicated responsibility to the system (Biswas et al., 2024; Möhlmann et al., 2023; Tarafdar et al., 2023; Wiener et al., 2023).

Proposition 3 (P3): Algorithmic evaluation that is opaque to the people it evaluates lowers perceived procedural fairness and trust in management.

Proposition 4 (P4): Algorithmic discipline delivered without a human interlocutor or a route of appeal has a stronger negative effect on trust than algorithmic direction or evaluation alone.

Direction, productivity and skill formation: the paradox. The experimental evidence on AI assistance is consistent: guidance raises immediate output and quality, with the largest gains for novices and lower-skilled workers (Brynjolfsson et al., 2025; Noy & Zhang, 2023). The same evidence base also shows the other side. When assistance does the reasoning, learners and practitioners perform better while assisted but worse once it is removed, and they often do not notice the decline (Bastani et al., 2025; Budzyń et al., 2025; Macnamara et al., 2024; Zhai et al., 2024). The reason is mechanical rather than motivational. Expertise is built through effortful retrieval, error and correction, and a system that prevents errors by prescribing each step also prevents the episodes in which tacit judgement forms. Organisations therefore face a skill-formation paradox: the configuration of algorithmic direction that maximises short-run productivity is the one that most suppresses the development of the expertise on which the organisation later depends, including the expertise needed to supervise, audit and recover from failures of the algorithm itself.

Proposition 5 (P5): Granular algorithmic direction is positively related to short-run task productivity and negatively related to skill formation; the positive effect is largest, and the negative effect most consequential, for novice workers.

Proposition 6 (P6): Skill formation mediates the relationship between algorithmic direction and long-run organisational capability, so that units with the largest short-run gains from granular direction will show the largest later losses in adaptability when the system fails, changes or is withdrawn.

Moderators. Two classes of condition change the strength of these effects. The first is design. Transparency about how scores are calculated, the ability to contest decisions with a human, and guidance that fades as

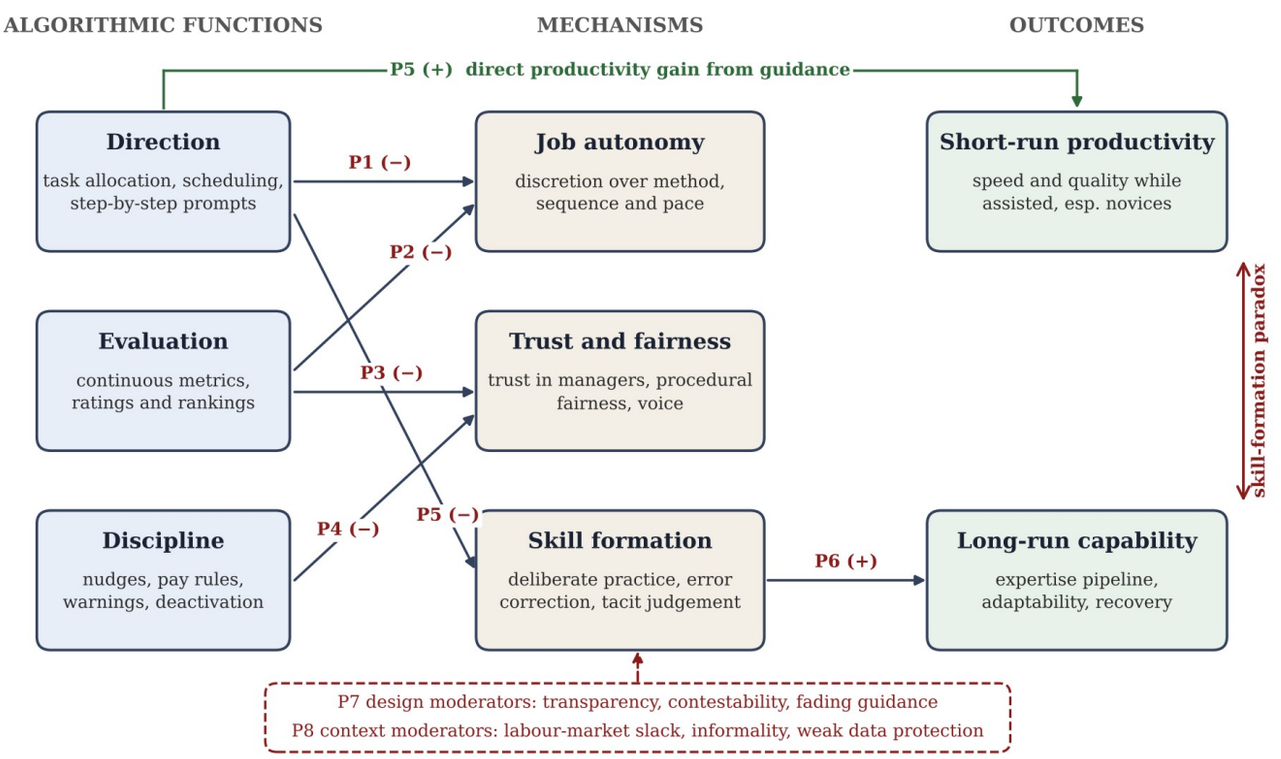
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competence grows (rather than remaining fixed) each target one of the mechanisms above (Bastani et al., 2025; Liang et al., 2023; Ravid et al., 2023; Semujanga & Parent-Rocheleau, 2024). The second is institutional. Where labour markets are slack, employment is informal and data-protection enforcement is weak, workers have little power to exit or to voice objection, and the costs of algorithmic control fall more heavily on them (Adekoya et al., 2025; Dinika, 2025; Ekdale & Aidoo, 2024).

Proposition 7 (P7): Transparency, contestability and fading guidance weaken the negative effects of algorithmic management on trust (P3, P4) and on skill formation (P5).

Proposition 8 (P8): Labour-market slack, informality and weak enforcement of data-protection rules strengthen the negative effects of algorithmic direction, evaluation and discipline on autonomy and trust.

Figure 1. Conceptual framework: functions of algorithmic management, mechanisms and outcomes (P = proposition)



Source: Developed by the author(s) from the integrative review. Solid arrows indicate proposed direct relationships; the dashed box indicates moderators.

4.1.3 Result 3: Design principles for AI-mediated supervision

The propositions imply five design principles for organisations that adopt algorithmic management and wish to keep its productivity benefits without hollowing out autonomy and expertise (Table 3).

Table 4. Design principles derived from the propositions

Principle	What it requires in practice	Mechanism addressed
1. Decompose before deploying	Decide separately whether to automate direction, evaluation and discipline; do not automate discipline by default	All (P1–P4)
2. Guidance that fades	Scaffold novices, then withdraw step-by-step prompts as competence is demonstrated; schedule unassisted practice	Skill formation (P5, P6)
3. Explain the score	Show workers which inputs drive their ratings and rankings, in plain language	Trust and fairness (P3)
4. Keep a human in the loop for sanctions	Route warnings, pay cuts and deactivation through a named manager with an appeal channel	Trust and voice (P4)
5. Measure what matters, and less of it	Limit monitoring to indicators tied to outcomes; review whether metrics crowd out learning and discretion	Autonomy (P2)

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4.2 DISCUSSION

The first research question asked which supervisory functions algorithmic systems take over and how each affects autonomy and trust. The decomposition answers that algorithmic systems absorb direction, evaluation and discipline separately, and that the evidence aligns with this separation. The negative association between algorithmic management and autonomy reported in survey research (Kinowska & Sienkiewicz, 2023; Parent-Rocheleau et al., 2024; Röttgen et al., 2025) is consistent with P1 and P2, and the meta-analytic finding that monitoring raises stress without improving performance (Ravid et al., 2023) supports the claim that evaluation carries costs that are not repaid in output. The decomposition also helps reconcile findings that otherwise look contradictory. Wiener et al. (2023) found that guiding forms of algorithmic control were seen as legitimate, and Semujanga and Parent-Rocheleau (2024) found that algorithmic compensation was associated with higher perceived procedural justice. Both results concern functions that are rule-based, visible and consistently applied. The framework predicts that the same workers will react very differently when a discipline function is opaque and cannot be appealed, which is what the qualitative studies of deactivation and sanctions report (Dinika, 2025; Möhlmann et al., 2023). Biswas et al. (2024) point to the same boundary: employees accept algorithms for formula-based judgements but want humans for discretionary ones. The implication for theory is that "algorithmic management" should not be modelled as a single exposure variable; its effects depend on which function is automated and on whether the worker can see and contest the logic behind it.

The second research question concerned skill formation. The productivity experiments (Brynjolfsson et al., 2025; Noy & Zhang, 2023) and the skill studies (Bastani et al., 2025; Budzyń et al., 2025; Rinta-Kahila et al., 2023) have been discussed in different literatures, but read together they describe the two sides of the paradox stated in P5 and P6. The groups who gain most from step-by-step guidance (novices and less experienced workers) are the groups whose expertise is still forming, and the mechanism that produces the gain, namely the removal of effortful problem solving, is the mechanism that suppresses learning (Macnamara et al., 2024). This extends algorithmic-management theory, which has focused on control and well-being, by adding a temporal dimension: the costs of algorithmic direction may be small today and large later, and they may be invisible to workers and managers alike. It also qualifies Cameron's (2024) finding that algorithmic management can give workers a sense of skill. The framework suggests that this felt skill may relate to navigating the system rather than to the transferable expertise the organisation needs when the system fails. The finding by Bastani et al. (2025) that safeguarded AI tutoring largely avoided learning losses is important, because it indicates that the paradox is a design problem rather than an inevitability; this is the basis of P7 and of the principle of guidance that fades.

The third research question concerned design and institutional conditions, with particular reference to African economies. The African studies reviewed describe workers who accept tight algorithmic control because alternatives are scarce (Adekoya et al., 2025), who rely on informal solidarity rather than formal voice to resist it (Ekdale & Aidoo, 2024), and whose autonomy is reduced across financial, task and behavioural dimensions (Dinika, 2025). These patterns are consistent with P8: where unemployment and informality are high and enforcement capacity is limited, exit and voice are weak, so the costs of algorithmic direction, evaluation and discipline fall more heavily on workers. The skill-formation paradox has an additional significance in these economies. Firms in Nigeria, Kenya, South Africa and elsewhere that adopt imported algorithmic systems for productivity reasons may raise output among young and inexperienced workers while slowing the development of the local managerial and technical expertise on which long-term competitiveness depends. Data-protection statutes now exist in several African countries, but the evidence reviewed suggests that rights on paper do not yet translate into transparency or contestability at the point where workers are scored and sanctioned. Firms, regulators and worker organisations therefore have a shared interest in the design principles in Table 4.

For managers and HR professionals, the framework turns the recommendations in Section 5 into an audit tool: the operationalisations in Table 2 can be used to check which functions a current system automates and, by comparing assisted with unassisted performance over time, to detect skill erosion before a system failure exposes it.

The study has limitations. As a conceptual paper it offers propositions, not tests. Its evidence base was restricted to journal articles published between 2023 and 2026; this ensured currency and verifiability but excluded older foundational works and the large volume of working papers in this fast-moving field. Several of the key skill studies come from education and medicine, so their transfer to other occupations needs to be tested. The African evidence is qualitative and concentrated in ride-hailing and delivery work. Future research should test P1 to P4 with function-level measures of algorithmic management, test P5 and P6 with longitudinal designs that compare assisted and unassisted performance, examine whether fading guidance preserves learning in organisational settings (P7), and conduct comparative

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studies across African labour markets with different levels of informality and regulatory enforcement (P8).

5. CONCLUSION AND RECOMMENDATION

This paper set out to explain what changes when supervision is mediated by algorithms. It concludes that algorithmic management is best understood as the separable automation of three supervisory functions (direction, evaluation and discipline), each of which affects employees differently. Granular direction narrows autonomy; continuous evaluation adds surveillance and, when opaque, undermines fairness; and automated discipline without a human interlocutor does the most damage to trust. Most importantly, the paper identifies a skill-formation paradox: the step-by-step algorithmic guidance that raises short-run productivity, especially for novices, also suppresses the practice through which expertise is formed, so that organisations may gain output today at the cost of capability later. These effects are moderated by design choices and by institutional context, and are likely to be stronger in labour markets, such as many in Africa, where workers have limited power to exit or to voice objection.

Five recommendations follow. First, organisations should decide separately whether to automate direction, evaluation and discipline, and should not automate discipline by default. Second, AI-assisted work systems should be designed so that guidance fades as competence grows, and should include protected time for unassisted practice. Third, workers should be told in plain language how their performance scores are produced. Fourth, sanctions such as pay deductions, warnings and deactivation should be reviewed by a named human manager, with an appeal channel. Fifth, regulators and industry bodies in African economies should translate existing data-protection provisions into enforceable workplace rights to explanation and human review of algorithmic decisions, and should support research that tracks skill formation among workers supervised by algorithms.

6. CONTRIBUTION TO EXISTING KNOWLEDGE

The paper makes four contributions. First, it offers a direction–evaluation–discipline decomposition of algorithmic management that replaces the treatment of algorithmic management as a single level of exposure with a function-specific account, and that reconciles apparently contradictory findings on legitimacy and fairness. Second, it connects the algorithmic-management literature with research on skill decay and cognitive offloading under AI assistance, and from that connection derives the skill-formation paradox, adding a long-run dimension to a field that has focused on immediate outcomes. Third, it states eight falsifiable propositions and proposes measures for each construct, providing an agenda for empirical work. Fourth, it extends theory on algorithmic management to African economies by specifying labour-market slack, informality and weak enforcement as moderators, and translates the framework into design principles that firms, regulators and worker organisations can apply.

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