Строително предприемачество и недвижима собственост
Construction Entrepreneurship and Real Property
ISSN (online): 2683-0280, https://cerp.ue-varna.bg

Integrating AI Education and Human Motivation for Sustainable Construction Productivity in Developing Nations

Samuel Nnadoziem NDUKUBA[1]

[1] ORCID iD 0000-0002-4161-213X, Department of ICT, IIE Rosebank College, Cape Town, South Africa, sndukuba@rosebankcollege.co.za

DOI: doi.org/10.56065/pfnyg615

JEL:
O33; J24; Q01; I25; D23; O15

Abstract:

Construction sites in developing nations are not short of problems, but two that rarely appear in the same analysis are the slow uptake of artificial intelligence and the persistent failure to motivate the workers who would use it. This paper argues that treating these as separate challenges is itself a root cause of the productivity stagnation that plagues the sector. A systematic literature review (SLR) was conducted using PRISMA guidelines, synthesising 28 peer-reviewed studies published between 2018 and 2026 and retrieved from Scopus, Web of Science, and Google Scholar. Thematic analysis produced three interlocking findings: AI education is a necessary but insufficient condition for productivity improvement; motivation determines whether skills acquired through training are ever applied on site; and sustainable productivity outcomes require both to operate simultaneously within a supportive institutional environment. A conceptual framework integrating these three dimensions is developed and theorised through the lens of socio-technical systems theory and human capital theory. The paper concludes with targeted recommendations for policymakers, construction firms, and academics working in resource-constrained contexts where neither technology nor motivation alone has moved the productivity needle.

Keywords:

AI, construction productivity, human motivation, education and sustainable construction

Now to cite:

Ndukuba, S. N. (2026). Integrating AI Education and Human Motivation for Sustainable Construction Productivity in Developing Nation. *Stroitelno predpriemachestvo i nedvizhima sobstvenost = Construction Entrepreneurship and Real Property, 3*(1), 143–158. https://doi.org/10.56065/pfnyg615

1. Introduction

Ask most construction managers in developing nations what stands between them and better productivity, and the answers cluster around a familiar list: labour that cannot do what the work requires, technology that no one knows how to use, and workers who have little reason to try harder than they already do. These are not new problems, but they are stubborn ones. Decades of policy attention, donor-funded training programmes, and now the arrival of AI-driven tools have not fundamentally altered the productivity trajectory of the sector in much of Sub-Saharan Africa, South Asia, or Southeast Asia (Ofori, 2015; Aghimien et al., 2020).

The question worth asking is whether the problem has been framed correctly. The dominant research tradition in this space treats technology adoption and workforce motivation as parallel but separate concerns. Studies on AI in construction focus on what the technology can do. This includes predictive analytics, automated scheduling, and real-time safety monitoring. Hence, without asking what conditions must exist for those tools to be used effectively and consistently by the workers they are designed to support (Pan & Zhang, 2021; Zhang & Jiang, 2026). Motivation research tends to determine wages, recognition, and working conditions as productivity levers. These are largely disconnected from the question of how motivated workers relate to digital systems and training opportunities (Johari & Jha, 2020; Weeks et al., 2025).

This paper argues that the separation is a mistake, analytically and practically. AI education without motivation produces workers who know what tools exist but do not use them; motivation without AI literacy produces committed workers operating below their potential in increasingly digitised environments. Neither gap is trivial. In developing nations, where labour informality, digital exclusion, and resource constraints amplify both problems, an integrated approach is not merely preferable; it is necessary (Xu et al., 2025; Okonkwo et al., 2025). Additionally, the existing literature has largely discussed the artificial intelligence (AI) integration and human motivation as separate domains. Studies by Zhang et al. (2021) and Zhang and Jiang (2026) on AI in construction primarily focus on technological adoption, automation, and process optimisation. Hence, there is limited attention to behavioural and human-centred factors influencing productivity to improve worker motivation. It is commonly known that motivation-based studies underline incentives, leadership, and behavioural determinants of labour productivity. This is often without considering digital transformation or AI-enabled systems as complementary enablers (Durdyev et al., 2021). However, despite growing interest in digital construction technologies, little research has examined how AI-enabled educational systems can be systematically integrated with motivational frameworks. Thus, to enhance sustainable productivity outcomes in construction environments during project delivery (Dolla et al., 2023).

This gap is a critical factor, particularly evident in developing nations such as South Africa, where structural inefficiencies, low technological readiness, and skills shortages further pressure productivity improvement efforts (Adekunle et al., 2021). Furthermore, barriers to digital transformation and workforce capability development have continued to worsen technological potential and human performance in construction projects (Ershadi & Lijauco, 2026). Consequently, there is a growing need for an integrated approach that combines AI-based

ISSN (online): 2683-0280, https://cerp.ue-varna.bg

education systems with human motivational strategies. This is to enhance sustainable construction productivity for the economic growth of the nation. This approach is expected to bridge the gap between technological capability and human performance. Therefore, improving both efficiency and long-term sustainability in construction project delivery. The study's objectives are threefold: to synthesise the existing evidence on AI education, human motivation, and construction productivity in developing-nation contexts; to identify the interactions between these dimensions that prior research has either missed or undertheorised; and to propose a conceptual framework that captures those interactions in a form that is practically actionable for firms, educators, and policymakers.

A systematic literature review was selected as the method because the problem is one of fragmented knowledge rather than absent knowledge. The evidence needed to build the integrated argument exists; it has simply not been assembled or interpreted through an integrative lens. The remainder of the paper is structured as follows: Section 2 reviews the theoretical context; Section 3 describes the SLR methodology; Section 4 presents the literature synthesis; Section 5 discusses findings; Section 6 presents the conceptual framework; Section 7 offers recommendations and future directions; and Section 8 concludes.)

2. Theoretical Context

2.1 Socio-Technical Systems Theory

The foundational theoretical lens for this paper is socio-technical systems theory, which holds that organisational performance is determined not by technical or human factors independently but by the quality of their interaction (Trist & Bamforth, 1951). Developed originally in the context of coal mining, a labour-intensive, hazardous environment not entirely unlike construction, the theory has proven generative across decades and industries because it resists the reductionism that plagues most technology-implementation thinking. In the AI adoption literature, socio-technical theory has been invoked to explain why technically superior systems frequently fail in practice: the social and organisational systems into which they are inserted are not designed to accommodate them (Oesterreich & Teuteberg, 2016). For construction in developing nations, this insight is particularly relevant. The barriers to AI adoption are not primarily technical; hardware is accessible, software is affordable, but social: workers lack training, managers lack trust in digital outputs, and organisations lack the incentive structures that would sustain behavioural change (Abioye et al., 2021; Xu et al., 2025).

2.2 Human Capital Theory

Human capital theory, most thoroughly developed by Becker (1993), holds that investment in education and training raises individual productivity by expanding the competencies that workers can deploy in economically valuable tasks. The theory is straightforward in its logic and well-supported empirically, but it rests on a behavioural assumption that deserves scrutiny in the present context: that workers who possess relevant skills will apply them. In environments where motivation is low, wages are irregular, recognition is absent, and career pathways are unclear, this assumption fails. Skills acquired through training lie dormant because there is no motivational architecture to activate them. This is precisely the situation documented in much of the developing-nation construction literature (Durdyev &

Mbachu, 2018; Ndukuba & Uwa, 2025). Human capital theory, in other words, is necessary but insufficient: it explains why education matters without explaining when the investment will be realised in practice.

2.3 Motivation Theory: From Herzberg to the Technology Context

The motivation literature relevant to this paper draws primarily on Herzberg's two-factor theory (1959), which distinguishes between hygiene factors, conditions whose absence creates dissatisfaction, but whose presence does not motivate, and genuine motivators, including achievement, recognition, and meaningful work. In construction, the absence of basic hygiene factors such as reliable wages, safe conditions, and job security is common in developing nations like sub-Saharan Africa. This creates a motivational floor below which no amount of AI education will produce productivity gains (Hosny et al., 2022; Weeks et al., 2025). More recently, the motivation literature has been extended into technology adoption contexts. Venkatesh et al. (2003), through the Unified Theory of Acceptance and Use of Technology (UTAUT), demonstrated that behavioural intention to use a technology itself is a function of motivational variables, including expected performance and social influence, which is the primary predictor of actual use. Therefore, the application of AI in construction indicates that motivating workers to engage with AI tools is not a soft skills concern secondary to technical know-how deployment but a precondition of it (Artemova, 2024; Neji et al., 2023).

3. Methodology

3.1 SLR Design and Rationale

This study adopts a systematic literature review (SLR) methodology, structured around the PRISMA 2020 guidelines (Page et al., 2021) and informed by the procedural framework of Tranfield, Denyer, and Smart (2003). The SLR was chosen because the research objective to synthesise and reinterpret fragmented evidence across AI education, human motivation, and construction productivity is better served by systematic synthesis than by primary data collection. An SLR surfaces patterns and relationships across studies that are invisible within any single study and makes the review process transparent and reproducible. The review question was defined using a PICOS framework: Population (construction workers, managers, and professionals in developing nations); Intervention (AI education programmes, motivational strategies, or their combination); Comparator (practice without structured AI education or motivation systems); Outcome (productivity, sustainability outcomes, technology adoption rates); Study design (peer-reviewed empirical and conceptual studies). This framework guided both the search strategy and the screening decisions.

3.2 Search Strategy

Electronic searches were conducted across five database engines. These are Scopus, Web of Science, Google Scholar, ScienceDirect, and Emerald Insight. This search was restricted to peer-reviewed publications from 2018 to 2026 in English. The core Boolean search string was:

("artificial intelligence" OR "AI education") AND ("construction productivity" OR "construction workforce") AND ("human motivation" OR "workforce training" OR "skills

ISSN (online): 2683-0280, https://cerp.ue-varna.bg

development") AND ("developing nations" OR "developing countries" OR "Global South").

Additional strings targeted each of the three thematic dimensions separately to ensure coverage. Backward and forward citation chasing was applied to landmark papers identified in the primary search.

3.3 Screening and Inclusion Criteria

The initial search returned 1,432 records. After de-duplication, 1,120 records were screened at the title and abstract level, reducing the pool to 357 potentially eligible studies. Full-text review produced 28 studies that met all inclusion criteria: peer-reviewed; English language; addressing AI education, human motivation, or construction productivity with relevance to developing-nation contexts; and published within the defined time window. Studies were excluded if they were non-English, lacked full text, addressed AI purely at the infrastructure or hardware level without workforce dimensions, or fell outside the construction and built environment domain. Quality was appraised using a five-criterion scoring rubric: clarity of objectives, methodological rigour, reliability of data, validity of findings, and contribution to knowledge, with studies scoring below three on five excluded from synthesis. This produced the 28 studies listed in Table 1.

3.4 Thematic Synthesis

Data extraction captured authors, year, country context, methodology, key findings, identified gaps, and theoretical grounding. Thematic synthesis followed Thomas and Harden's (2008) three-stage process: line-by-line coding of findings sections; aggregation of codes into descriptive themes; and generation of analytical themes that moved beyond description to interpretation. Three primary analytical themes emerged: AI education and skills development; human motivation and workforce engagement; and sustainable productivity outcomes.

4. Literature Synthesis

Table 1. Literature Synthesis on AI Education, Human Motivation, and Construction Productivity

Author(s) & Year	Key Findings	Research Gap	Contribution to Body of Knowledge
Abioye et al. (2021)	AI improves automation and decision-making in construction; workforce skill deficits constrain adoption.	Does not examine how education systems should be restructured to build these skills.	Establishes AI's transformative potential while surfacing the human-capital barrier central to this study.
Aghimien et al. (2020)	Robotics research in construction is growing rapidly, but uptake in developing nations remains minimal.	Does not address motivational or educational conditions that determine adoption.	Locates the developing-nation adoption gap that frames this paper's problem statement.
Artemova (2024)	AI can enhance learner motivation in educational settings when aligned with activity theory principles.	Empirical evidence is limited; construction workforce applications are unexplored.	Provides a conceptual bridge between AI tools and motivational mechanisms in learning environments.

Author(s) & Year	Key Findings	Research Gap	Contribution to Body of Knowledge
Awad et al. (2021)	Lean construction improves productivity but operates largely independently of AI integration.	Sustainability outcomes of lean-AI convergence are not modelled.	Supports the case for coupling efficiency technologies with human-centred management strategies.
Becker (1993)	Investment in education raises individual productivity and broader economic output — the human capital thesis.	Pre-digital; does not engage with AI-driven learning or digital skills formation.	Provides the foundational economic logic for investing in AI education as a productivity lever.
Durdyev & Mbachu (2018)	Labour shortages and poor skills are identified as primary productivity constraints in developing-country construction.	Motivational dimensions of the skill-productivity relationship are not examined.	Contextualises the human-capital challenge in environments where this study's framework is most needed.
Elkington (1997)	Sustainable development requires simultaneous economic, environmental, and social returns — the triple bottom line.	Pre-AI does not consider how digital transformation intersects with sustainability imperatives.	Anchors the study's definition of sustainable productivity within an internationally recognised framework.
Hasan et al. (2018)	A thirty-year review confirms that construction productivity challenges persist despite technological advances.	Does not disaggregate findings by national development context.	Demonstrates the durability of the problem and strengthens the justification for integrated solutions.
Herzberg (1959; 1968)	Productivity is shaped by two distinct factor sets: hygiene factors that prevent dissatisfaction and motivators that drive performance.	Does not engage with technological change as a motivational context.	Provides the motivational theory underpinning this study's analysis of workforce engagement with AI tools.
Hosny et al. (2022)	Empirical evidence that labour motivation directly and significantly improves construction productivity on site.	Does not examine the role of technology or digital training in shaping motivational outcomes.	Validates the motivation-productivity relationship the framework relies on.
Johari & Jha (2020)	Strong positive correlation confirmed between work motivation and construction labour productivity across study sites.	AI and digital learning environments are outside the study's scope.	Provides recent empirical grounding for treating motivation as a first-order productivity variable.
Maslow (1943)	Human needs operate hierarchically; higher-order needs drive performance once basic needs are met.	Does not address how technological change restructures the need hierarchy.	Supplies the psychological foundation for the motivational logic embedded in the proposed framework.
Muse et al. (2025)	BIM-based frameworks can mitigate construction disputes and improve project performance.	AI integration with BIM and motivational dimensions are not addressed.	Illustrates how digital tools can reshape project dynamics, supporting the case for AI-education investment.
Neji et al. (2023)	AI-based tools enhance student motivation, but practical frameworks for implementation are absent.	The evidence base is thin; construction-specific applications are not explored.	Links AI deployment to improved learning motivation, reinforcing a core mechanism in the proposed framework.

Author(s) & Year	Key Findings	Research Gap	Contribution to Body of Knowledge
Ndukuba et al. (2025)	Empowerment-driven motivation significantly raises worker productivity; incentives and organisational support are key enablers.	Limited to a single context; scalability across developing nations is untested.	Provides context-specific evidence directly connecting motivation strategies to productivity outcomes.
Ndukuba & Uwa (2024)	Strong motivation-performance relationship confirmed; gaps in how motivational strategies are implemented in practice.	Does not examine AI education as a complementary productivity driver.	Strengthens the empirical foundation for the human-motivation strand of the integrated framework.
Oesterreich & Teuteberg (2016)	Digitalisation in construction faces resistance rooted in skill deficits and cultural inertia.	Human motivation as a driver of digital adoption is not modelled.	Contextualises the human barriers to AI adoption that the educational and motivational framework addresses.
Ofori (2015)	Structural and institutional weaknesses — not just workforce issues — constrain construction development in the Global South.	Does not engage with digital transformation as a structural solution.	Provides macro-level framing of the developing-nation construction context.
Oke et al. (2023)	Environmental and economic sustainability practices are shaped by organisational and individual behavioural drivers.	AI's role in enabling sustainable practices is not examined.	Supports the integration of sustainability into the productivity framework beyond simple efficiency metrics.
Okonkwo et al. (2025)	AI integration in construction education raises student confidence and perceived career relevance.	Industry alignment of curriculum changes is not evaluated.	Demonstrates that AI education produces measurable human-factor benefits relevant to workforce readiness.
Onatayo et al. (2024)	Generative AI is reshaping AEC practice, creating urgent upskilling demands that curricula have not yet met.	Motivational conditions for workforce engagement with AI upskilling are underexplored.	Reinforces the argument that AI education must be deliberately designed rather than assumed to occur organically.
Pan & Zhang (2021)	AI improves project performance across multiple construction functions; integration challenges remain significant.	Human and motivational dimensions of AI adoption are outside the study's scope.	Provides a comprehensive technical baseline for AI's construction productivity potential.
Trist & Bamforth (1951)	Organisational performance depends on the co-design of social and technical systems — neither alone is sufficient.	Pre-digital theory; application to AI-driven environments requires conceptual extension.	Provides the socio-technical systems rationale for treating AI education and human motivation as jointly necessary.
Venkatesh et al. (2003)	Technology adoption is predicted by behavioural intention and facilitating conditions — the UTAUT model.	Does not address the educational antecedents of behavioural intention.	Supplies the technology acceptance framework through which the study analyses AI adoption readiness.
Weeks et al. (2025)	Human factors — including motivation and stress — significantly influence both productivity and safety outcomes on construction sites.	AI-mediated learning as a human-factor intervention is not examined.	Extends the motivation-productivity link to include safety outcomes, broadening the framework's relevance.

Author(s) & Year	Key Findings	Research Gap	Contribution to Body of Knowledge
Xu et al. (2025)	AI is catalysing a workforce transformation from manual skill to digital intelligence in construction.	Motivational and educational enablers of this transition are not modelled.	Introduces the smart-workforce concept that the study's framework is designed to operationalise.
Yap et al. (2026)	Communication barriers in construction projects significantly reduce productivity; contractor-side factors are underweighted.	AI-assisted communication tools are not evaluated.	Highlights a productivity constraint that AI tools are well-positioned to address, supporting the integration argument.
Zhang & Jiang (2026)	AI adoption in construction has grown rapidly over five years, but implementation remains fragmented.	An integrated framework combining human and technological dimensions is explicitly identified as absent.	Directly validates the gap this study addresses and confirms the timeliness of an integrated productivity framework.

Source: Author's own development

5. Discussion of Findings

5.1 Construction Productivity in Developing Nations: A Problem with Two Faces

The literature is consistent on the scale of the productivity problem but less consistent on its nature. Most studies point to either technical deficits, outdated methods, poor planning, inadequate equipment, or human deficits, low skills, high turnover, or weak supervision as the primary culprit (Hasan et al., 2018; Ofori, 2015). The review findings suggest this dichotomy is misleading. In developing-nation contexts, the two deficits are structurally connected: technical systems fail because the humans operating them are undertrained and undermotivated, and human performance deteriorates partly because the technical environments workers inhabit are chaotic and unsupportive (Weeks et al., 2025; Durdyev & Mbachu, 2018). This systemic reading of the productivity problem has a direct methodological implication. Studies that model productivity as a function of individual variables, skills alone, motivation alone, or AI tools alone will consistently underestimate the size of the improvement that is possible and misidentify the intervention point. Motivational interventions produce significant productivity gains, but these gains are larger and more durable once workers have the technical competencies to harness their effort successfully during project delivery (Ndukuba et al., 2025, and Ndukuba and Uwa, 2025).

5.2 AI in Construction: Potential Without Activation

The indication of AI's construction productivity approaching is substantial and growing (Pan & Zhang, 2021; Zhang & Jiang, 2026). Machine learning models outperform traditional estimation techniques on cost and schedule prediction. Additionally, computer vision systems detect safety hazards faster and more reliably than manual inspection. While natural language processing tools improve document management and site communication. These are real productivity gains, not speculative ones. Similarly, the literature documents that with equal consistency, gains are realised only where workforce readiness exists (Abioye et al., 2021; Xu et al., 2025). In developing nations like South Africa, where digital literacy baselines are lower. This makes the AI training infrastructure thinner; the readiness gap is often decisive. Construction firms that acquire AI tools without investing in workforce preparation find that adoption is superficial; the tool is present, used occasionally, and never integrated into daily practice in ways that compound over time (Onatayo et al., 2024). This is not a technology problem; it is a human problem, and the human problem has two distinct components: competence and motivation.

5.3 AI Education: Necessary but Not Self-Activating

It is critical to consider training programmes that build AI competency in construction workforces to produce measurable improvements in knowledge. Thus, building workers' confidence and willingness to engage with digital systems (Okonkwo et al., 2025; Neji et al., 2023). These are important outcomes. But the review reveals a consistent finding that sits underneath the positive headline results: training effects are strongest among workers who entered the programme already motivated workers who saw the training as relevant to their careers, valued by their employers, and connected to tangible rewards. Workers who attended training under compulsion, or without organisational signals that newly acquired skills would be recognised and used, showed weaker and less durable learning outcomes. Artemova (2024) makes this argument theoretically through an activity-theory lens; Onatayo et al. (2024) document it empirically in generative AI upskilling contexts. The implication is uncomfortable for education advocates: AI education is necessary but not self-activating. It requires a motivational substrate to produce the outcomes that human capital theory predicts.

5.4 Motivation: The Variable That Determines Whether Everything Else Works

The motivation findings in this review are among the most robust in the corpus. Johari and Jha (2020) confirm a strong positive relationship between work motivation and labour productivity. Hosny et al. (2022) show that motivational interventions creäte measurable productivity advancements on construction sites. Similarly, a study by Weeks et al. (2025) extends the finding to safety outcomes. This shows that motivated workers are not only more productive but also less injury-prone, a significantly important factor in high-hazard environments. Similarly, according to studies by Venkatesh et al. (2003) and Muse et al. (2025), motivation predicts technology acceptance. Workers who are motivated by recognition, career development, and a sense that their organisation values their growth are more likely to engage seriously with AI training, more likely to apply what they learn, and more likely to persist through the early period of friction that any new tool creates. Motivation, in this reading, is not a parallel driver of productivity alongside AI education it is the condition that determines whether AI education produces any return at all.

5.5 Sustainable Productivity: The Long Game

Short-term productivity gains from AI tools or motivational interventions are relatively easy to demonstrate. Sustainable productivity that improves over time will survive management changes. Also, producing environmental and social co-benefits alongside economic efficiency is considerably harder to build (Awad et al., 2021; Oke et al., 2023). The review evidence recommends that the sustainability of productivity increases is directly proportional to the depth of integration between

AI education and motivational structures within the organisation. Therefore, training programmes are one-off events, and motivation is treated as a periodic management concern. These productivity improvements tend to be temporary. Where organisations build continuous learning environments. It is crucial to build AI skills development that is ongoing, with feedback loops surrounding daily work. These motivational conditions are actively maintained as the evidence points to compounding returns (Xu et al., 2025; Zhang & Jiang, 2026).

6. Conceptual Framework

6.1 Framework Overview

The framework proposed here is built around three interlocking components: AI education and digital skills formation; human motivation and organisational enablement; and sustainable productivity outcomes. These components do not operate in sequence: AI education first, then motivation, then productivity, but simultaneously and interdependently. The framework's central claim, supported by the evidence reviewed, is that neither AI education nor motivation produces sustainable productivity in isolation; only their co-activation within a supportive institutional environment generates the compounding returns that the sector requires. The framework is theorised through two theoretical lenses. Socio-technical systems theory (Trist & Bamforth, 1951) provides the rationale for treating the technological and human components as co-determinants: an AI-education system that ignores motivational dynamics will fail for the same reason that a technical coal-getting system that ignored social organisation failed in Trist and Bamforth's original study. Human capital theory (Becker, 1993) provides the rationale for investment: education raises productivity, but only when the conditions for activating acquired skills are in place.

6.2 Component One: AI Education and Digital Skills Formation

This component encompasses the structured, intentional development of the digital competencies that construction workers need to engage productively with AI tools. In developing-nation contexts, most AI education frameworks in the literature require basic digital literacy. Also, data familiarity and comfort with algorithmic outputs must precede more sophisticated AI-specific training (Onatayo et al., 2024; Okonkwo et al., 2025). The framework indicates three dimensions of AI education that are critical to be addressed simultaneously. Technical competency covers the skills to operate AI tools. This includes inputting data, interpreting outputs, and identifying errors. Conceptual understanding of why AI tools make the predictions and recommendations as they do. The sufficient to evaluate outputs critically rather than accept them uncritically. Lastly, adaptive capacity covers the ability to learn new AI tools as the technology evolves, which in a rapidly changing field is arguably the most valuable competency of the three (Xu et al., 2025; Pan & Zhang, 2021).

6.3 Component Two: Human Motivation and Organisational Enablement

The motivational component of the framework operates at two levels. At the individual level, it addresses the intrinsic and extrinsic motivational factors that Herzberg (1959) and Maslow (1943) identified, adapted to the specific conditions of construction work in developing nations: the hygiene factors reliable wages, safe conditions, job security that must be satisfied before higher-order motivators can function, and the performance motivators recognition, meaningful work, career development that drive discretionary effort and engagement with learning. At the organisational level, the framework calls for what Ndukuba et al. (2025) term empowerment-driven motivation: the creation of structural conditions, participatory management, transparent performance recognition, investment in training as a visible signal of worker value, that sustain individual motivation over time. Without the organisational dimension, individual motivational interventions produce temporary effects that dissipate when the immediate stimulus is removed. It is the organisational architecture of motivation that converts episodic engagement with AI tools into habitual practice.

6.4 Component Three: Sustainable Productivity Outcomes

The productivity outcomes the framework targets are explicitly defined in triple-bottom-line terms (Elkington, 1999): economic efficiency (output per unit of input, project delivery performance), environmental performance (waste reduction, resource optimisation, both areas where AI tools are documented contributors), and social outcomes (worker wellbeing, equitable skill development, reduced occupational harm). Defining productivity this way is not academic expansiveness; it reflects the actual conditions under which sustainable productivity must be demonstrated and measured in developing-nation contexts where donor funding, government procurement, and international partnership increasingly require social and environmental accountability alongside financial performance (Oke et al., 2023).

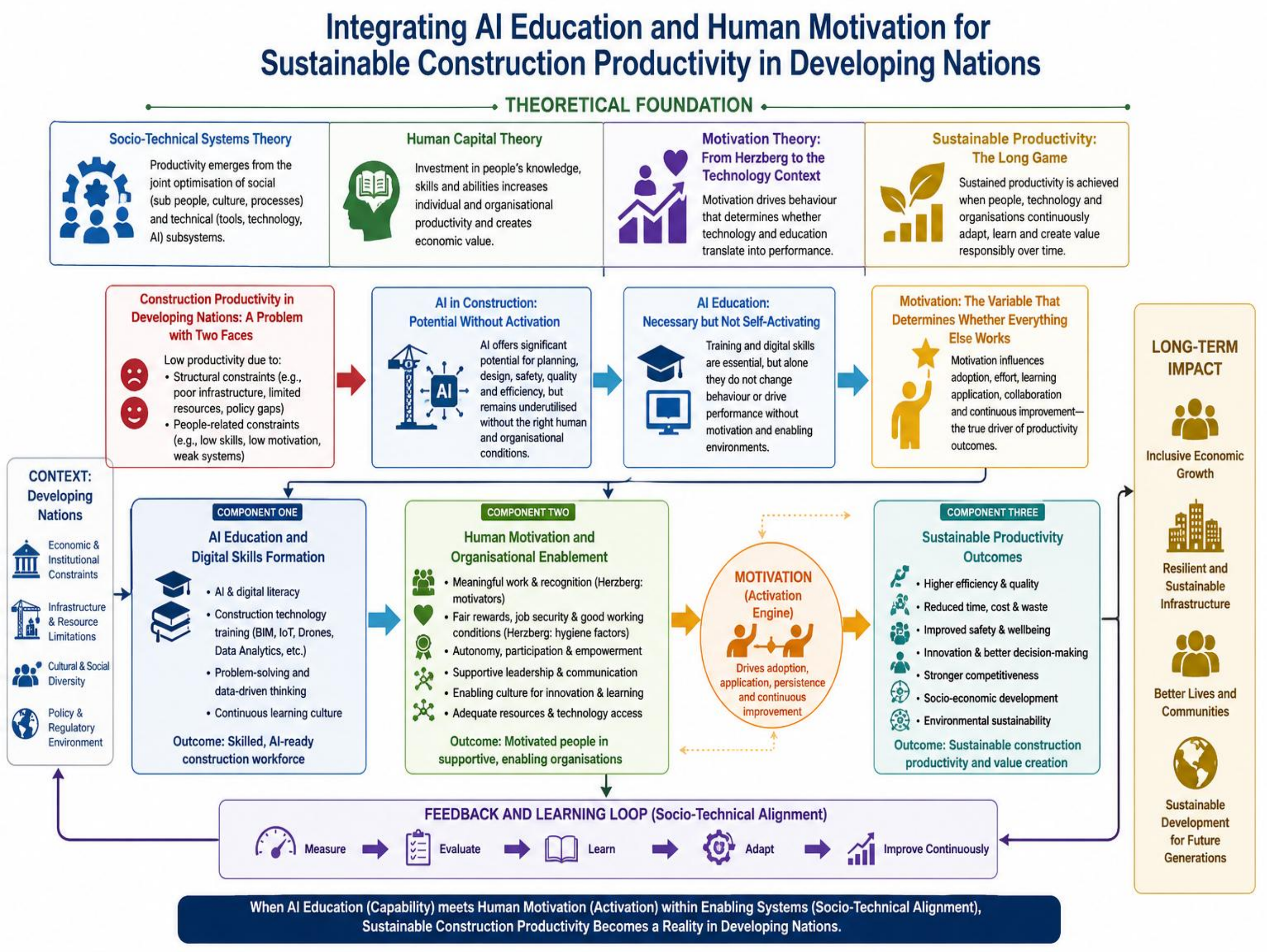
6.5 The Integration Mechanism

The mechanism through which the three components interact is a feedback loop rather than a one-way causal chain. AI education raises competency and, when delivered in ways that signal organisational investment, reinforces motivation. Motivation raises engagement with AI training and the quality of skill application on-site. Sustainable productivity outcomes, when recognised and attributed to the combined investment, reinforce both the organisational commitment to AI education and the individual motivation to continue learning. Breaking any link in this loop, underfunding education, neglecting motivation, or defining productivity too narrowly to capture the full return interrupts the compounding dynamic the framework is designed to generate.

Figure 1 presents the proposed conceptual framework, illustrating the interrelationships among AI education, human motivation, organisational enablement, sustainable productivity outcomes, and the reinforcing feedback mechanisms supporting long-term construction productivity in developing nations.

ISSN (online): 2683-0280, https://cerp.ue-varna.bg

Figure 1. Conceptual Framework for Integrating AI Education, Human Motivation and Sustainable Construction Productivity in Developing Nations



Source: Author's own development with the assistance of artificial intelligence (ChatGPT)

7. Recommendations

7.1 For Governments and Policymakers

The framework's institutional dimension requires policy support that most developing nations have not yet provided. Governments should integrate AI competency requirements into construction professional licensing frameworks and mandate that AI-focused curricula are embedded in construction management and vocational training programmes, not as electives but as core content. Public infrastructure procurement can be leveraged directly: requiring evidence of AI-trained workforces as a tender evaluation criterion would create powerful institutional incentives that internal advocacy rarely generates. Regulatory frameworks governing construction practice should be updated to acknowledge AI-assisted decision-making and provide guidance on liability when AI outputs inform site decisions. Without this clarity, firms in developing nations, already risk-averse in relation to new technology, will have an additional reason to delay adoption.

7.2 For Construction Firms

Firms that treat AI education as a cost rather than an investment will underperform against those that treat it as a capability-building strategy. The evidence reviewed is clear that AI tools deliver returns proportional to workforce readiness and that workforce readiness is built through training combined with motivational environments that make learning feel worthwhile. Practical priorities include continuous rather than episodic training programmes; mentorship pairings between AI-competent and AI-novice workers; and transparent performance recognition systems that attribute productivity gains to the workers who drove them. Motivational conditions, such as reliable wages, safe environments, and career development pathways, must be treated as preconditions for AI investment, not as separate management concerns. Firms that deploy AI tools into poorly motivated workforces are funding an experiment that the evidence suggests will fail.

7.3 For Educators and Researchers

Construction management and vocational curricula in developing nations need urgent revision to incorporate AI literacy at multiple levels of sophistication. Universities producing construction professionals are producing graduates who will manage AI-assisted sites within five years of graduation; the absence of AI education from these programmes is already a preparation gap, not a future one (Onatayo et al., 2024; Okonkwo et al., 2025). Future research should focus on empirically validating the integrated framework proposed here using structural equation modelling (SEM) with primary data from multiple developing-nation contexts. Longitudinal studies tracking whether AI education and motivational investments produce the compounding productivity returns that the framework predicts would substantially strengthen the evidence base. Comparative work across different institutional environments, different regulatory contexts, different labour market structures, and different digital infrastructure baselines would illuminate which elements of the framework are universally applicable and which require contextual adaptation.

8. Conclusions

This study ascertained that barriers to digital transformation and workforce capability development have continued to worsen technological potential and human performance in construction projects. Therefore, there is a growing need for an integrated approach that combines AI-based education systems with human motivational strategies. This is to enhance sustainable construction productivity for the economic growth of the nation. This approach is expected to bridge the gap between technological capability and human performance. The construction sector in developing nations will not become more productive simply because AI tools become cheaper and more accessible. Tools require people, and people require both the competency to use them and the motivation to bother. This paper has argued, based on a systematic review of 28 peer-reviewed studies, that these three requirements, AI education, human motivation, and the institutional conditions that sustain both, are not additive but multiplicative. The absence of anyone suppresses the returns from the others.

The conceptual framework developed here is a practical response to that diagnosis. It does not propose new technology or new motivational theory; it proposes a different way of organising what already exists: AI education systems, motivational management practices, and institutional support structures so that they reinforce rather than operate in ignorance of one another. In environments where resources are genuinely scarce and the cost of failed implementation is high, integration is not an academic refinement. It is the difference between AI investment that compounds and AI investment that sits idle on a shelf. The sector in Sub-Saharan Africa, South Asia, and across the developing world deserves better than imported solutions designed for better-resourced contexts. The framework offered here is a step toward something more contextually honest and, the evidence suggests, more likely to work.

References

Abioye, S. O., Oyedele, L. O., Akanbi, L. A., Ajayi, A. O., Delgado, J. M. D., Bilal, M., & Akinade, O. O. (2021). Artificial intelligence in the construction industry: A review of present status, opportunities and future challenges. *Journal of Building Engineering, 44*, 103299. https://doi.org/10.1016/j.jobe.2021.103299

Adekunle, S. A., Ejohwomu, O., & Aigbavboa, C. O. (2021). Building information modelling diffusion research in developing countries: a user meta-model approach. *Buildings, 11*(7), 264.

Aghimien, D. O., Aigbavboa, C. O., Oke, A. E., & Thwala, W. D. (2020). Mapping out research focus for robotics and automation research in construction-related studies: A bibliometric approach. Journal of Engineering, Design and Technology, 18(5), 1063–1079.

Artemova, I. (2024). Bridging motivation and AI in education: An activity theory perspective. *Digital Education Review, 45*, 59–69.

Awad, T., Guardiola, J., & Fraíz, D. (2021). Sustainable construction: Improving productivity through lean construction. *Sustainability, 13*(24), 13877.

Becker, G. S. (1993). Human capital: A theoretical and empirical analysis, with special reference to education (3rd ed.). University of Chicago Press.

Dolla, T., Jain, K., & Delhi, V. S. K. (2023). STRATEGIES FOR DIGITAL TRANSFORMATION IN CONSTRUCTION PROJECTS: STAKEHOLDERS' PERCEPTIONS AND ACTOR DYNAMICS FOR INDUSTRY 4.0. *Journal of Information Technology in Construction, 28*.

Durdyev, S., & Mbachu, J. (2018). Key constraints to labour productivity in residential building projects: Evidence from Cambodia. *International Journal of Construction Management, 18*(5), 385–393.

Durdyev, S., Mbachu, J., Thurnell, D., Zhao, L., & Hosseini, M. R. (2021). BIM adoption in the Cambodian construction industry: key drivers and barriers. *ISPRS International Journal of Geo-Information, 10*(4), 215.

Elkington, J. (1999). Cannibals with forks: The triple bottom line of 21st century business. Capstone Publishing.

Ershadi, M., & Lijauco, F. (2026). A framework for digitalizing construction businesses: drivers, barriers and outcomes. *Smart and Sustainable Built Environment*, *15*(1), 120–155.

Hasan, A., Baroudi, B., Elmualim, A., & Rameezdeen, R. (2018). Factors affecting construction productivity: A 30-year systematic review. *Engineering, Construction and Architectural Management, 25*(7), 916–937.

Herzberg, F. (1959). The motivation to work. John Wiley & Sons.

Herzberg, F. (1968). One more time: How do you motivate employees? *Harvard Business Review, 65*, 53–62.

Hosny, S., Abdel-Aziz, N., & Hossny, H. E. (2022). Assessment of the effect of labour motivation on construction productivity. *NeuroQuantology, 20*(8), 3888–3903.

Johari, S., & Jha, K. N. (2020). Impact of work motivation on construction labour productivity. *Journal of Management in Engineering, 36*(5), 04020052.

Maslow, A. H. (1943). A theory of human motivation. *Psychological Review, 50*(4), 370–396.

Muse, A. B., Alsuhaibani, A., Hassanain, M. A., Alshibani, A., & Muse, A. M. (2025). Framework for leveraging BIM to mitigate disputes in construction projects in Saudi Arabia. *Frontiers in Built Environment, 11*, 1719589.

Nawari, N. O. (2020, July). Blockchain technologies: Hyperledger fabric in BIM work processes. In *International Conference on Computing in Civil and Building Engineering* (pp. 813–823). Springer International Publishing.

Ndukuba, S. N., & Aghaegbulam, U. C. (2025). Examining the motivation-performance link among construction employees in Western Cape, South Africa. *AI and Data Science Journal, 2*(1), 8–17. https://doi.org/10.61784/adsj3007

Ndukuba, S. N., Simpeh, E. K., & Kumar, P. (2025). Revolutionizing Worker Productivity Through Empowerment-Driven Motivation in South Africa's Construction Industry. *Construction Entrepreneurship and Real Property, 2*(2), 47–65.

Neji, W., Boughattas, N., & Ziadi, F. (2023). Exploring new AI-based technologies to enhance students' motivation. *Issues in Informing Science & Information Technology, 20*, 113–128.

Oesterreich, T. D., & Teuteberg, F. (2016). Understanding the implications of digitisation and automation in the context of Industry 4.0. *Computers in Industry, 83*, 121–139.

Ofori, G. (2015). Nature of the construction industry, its needs and its development: A review of four decades of research. *Journal of Construction in Developing Countries, 20*(2), 115–135.

Oke, A. E., Aliu, J., Odia, O. A., Aigbavboa, C. O., Jamir Singh, P. S., Awuzie, B. O., & Samsurijan, M. S. (2023). A quantitative assessment of key drivers for environmental economic practices adoption for sustainable development. *Sustainable Development, 31*(5), 3579–3594.

Okonkwo, C., Lan, R., Awolusi, I., & Cai, J. (2025). Integrating artificial intelligence into construction education: Assessing the impact on students' perception of knowledge, confidence, and relevance to career. *Journal of Construction Engineering and Management, 151*(3), 04024185.

Onatayo, D., Onososen, A., Oyediran, A. O., Oyediran, H., Arowoiya, V., & Onatayo, E. (2024). Generative AI applications in architecture, engineering, and construction: Trends, implications for practice, education, and imperatives for upskilling — a review. *Architecture, 4*(4), 877–902.

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ, 372*, n71. https://doi.org/10.1136/bmj.n71

Pan, Y., & Zhang, L. (2021). Roles of artificial intelligence in construction engineering and management: A critical review and future trends. *Automation in Construction*, *122*, 103517.

Thomas, J., & Harden, A. (2008). Methods for the thematic synthesis of qualitative research in systematic reviews. *BMC Medical Research Methodology*, *8*(1), 45.

Tranfield, D., Denyer, D., & Smart, P. (2003). Towards a methodology for developing evidence-informed management knowledge by means of systematic review. *British Journal of Management, 14*(3), 207–222.

Trist, E. L., & Bamforth, K. W. (1951). Some social and psychological consequences of the longwall method of coal-getting. *Human Relations, 4*(1), 3–38.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478.

Weeks, K., Safa, M., & Zamiran, S. (2025). The productivity–safety nexus: The impact of human factors on operational efficiency in construction projects. *Buildings, 16*(1), 87.

Xu, X., Arshad, M. A., He, Y., Liu, H., Chen, Q., & Yang, J. (2025). From skilled workers to smart talent: AI-driven workforce transformation in the construction industry. *Buildings, 15*(14), 2552.

Yap, J. B. H., Yu, C. Y., Skitmore, M., & Lee, C. Y. (2026). Lost in transmission: Uncovering communication barriers in construction through the contractor's lens. *International Journal of Construction Management,* 1–19. https://doi.org/10.1080/15623599.2024.2345678

Zhang, J., & Jiang, S. (2026). Review of artificial intelligence applications in construction management over the last five years. *Engineering, Construction and Architectural Management, 33*(1), 361–379.

Zhang, S., Liu, K., & Li, X. (2021). Artificial intelligence in construction engineering and management. *Automation in Construction, 130*, 103844. https://doi.org/10.1037/000015700