From Efficiency to Capability Development: Assessing AI-Enabled Work Transformation in SMEs

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ABSTRACT

Small and medium-sized enterprises (SMEs) play a critical role in global value chains but often face structural and resource-based constraints that limit their ability to benefit from artificial intelligence (AI)-driven supply chain innovations. From the perspective of global development theories, these constraints reflect restricted capability sets and unequal developmental trajectories rather than purely technical or financial limitations. While most research emphasizes AI's performance and productivity benefits, this study examines how AI-enabled processes extend beyond efficiency gains to influence human and organizational capability development, particularly in terms of agency, opportunity, and contextual adaptability. It introduces the concept of Developmental Capability Intensity (DCI), capturing the extent to which AI expands individuals' substantive freedoms rather than merely automating tasks. The study develops and pilots an evaluative framework to assess the developmental orientation of AI in SMEs, contributing to more inclusive and responsible digital transformation aligned with human and organizational development.

Keywords: SMEs, AI, Sustainable Supply Chain, Capability Approach, Responsible AI.

1. INTRODUCTION

Small and medium-sized enterprises (SMEs) are the backbone of the global economy, representing over 90% of businesses worldwide and contributing substantially to employment and value creation (Kot, 2018). Their significance extends beyond aggregate economic output. As specialized, agile, and knowledge-rich nodes within global value chains, SMEs enhance the resilience and adaptability of supply networks, enabling rapid responses to market volatility, geopolitical disruptions, and environmental pressures (Younis et al., 2021; Tukamuhabwa et al., 2015; Pessot et al., 2023).

This developmental role is also reflected in SMEs' contributions to social and environmental progress. Grounded in close stakeholder relationships and owner-manager values, many SMEs align with Triple Bottom Line (TBL) principles, embracing ethical labor practices, community engagement, and environmentally conscious operations (Carter & Rogers, 2008; Seuring & Müller, 2008; Kot, 2018).

The diffusion of artificial intelligence (AI) and data analytics within Industry 4.0 presents both an unprecedented opportunity and a profound paradox for SMEs. While AI promises efficiency, predictive capability, and enhanced supply chain resilience (Collins et al., 2021; Dash et al., 2019), SMEs remain disproportionately excluded due to high costs, technical skill shortages, weak data infrastructure, and limited integration capacity (Alhasawi et al., 2023; Guo, 2023). These barriers risk deepening existing inequalities, turning AI from a potential enabler of SME innovation into a force that reinforces large-firm dominance (Qureshi, 2023).

Beyond these adoption challenges, AI is fundamentally reshaping the nature of work. It is not only changing what SMEs do, but also how work is structured, how decisions are made, and how human capabilities evolve over time. In this context, a critical question emerges: are AI-enabled systems primarily deployed as tools for efficiency, or do they transform work by expanding or constraining human and organizational capabilities? This question is particularly salient for SMEs, where work is closely tied to entrepreneurial agency, contextual knowledge, and adaptive decision-making.

Prevailing AI models, typically designed for large-firm contexts and driven by efficiency logic, risk undermining these capabilities. They may erode entrepreneurial autonomy, overlook the contextual knowledge of owner-managers, and embed standardized decision logics that are misaligned with local realities. Moreover, concerns around algorithmic bias and data asymmetries raise further challenges, potentially reinforcing structural inequalities and limiting inclusive development (O'Neil, 2017; Qureshi, 2023; Sahay et al., 2025). Despite growing interest in AI-enabled supply chains, there is limited research that systematically evaluates how AI reshapes work in SMEs, particularly in terms of capability formation, agency, and opportunity expansion.

To address this gap, this research adopts a design science perspective (Gregor & Hevner, 2013), recognizing the need to both conceptualize and operationalize developmental assessment. It introduces the concept of Developmental Capability Intensity (DCI) and develops an evaluative framework for assessing the developmental orientation of AI-enabled processes in SMEs. By focusing on capability expansion rather than performance alone, the study aims to provide a structured approach to understanding how AI transforms work systems over time.
Accordingly, the study is guided by the following research questions:

RQ1: *To what extent are AI-enabled systems deployed as efficiency-enhancing tools, versus transformative systems that expand or constrain human and organizational capabilities?*

RQ2: *How can the developmental impact of AI-enabled processes in SMEs be systematically assessed in terms of their effects on human and organizational capabilities?*

2. LITERATURE REVIEW

This literature review examines research at the intersection of AI, SME development, and global supply chains, moving beyond techno-optimistic narratives to uncover underlying challenges and contradictions. To unpack the AI promise paradox facing SMEs, it adopts a multi-dimensional perspective integrating techno-economic, human-centered, and socio-technical theories, grounded in the normative development approach of Hall and Midgley (2004). We synthesize three complementary clusters of theories: (1) foundational business and supply chain theories explaining adoption and performance; (2) human development and critical theories emphasizing agency and equity; and (3) integrative frameworks capturing socio-technical and process dynamics across levels of analysis.

2.1 Foundational Business & Supply Chain Theories

AI in supply chain management (SCM) is largely framed through strategic management theories. The Resource-Based View (RBV) conceptualizes AI capabilities, data assets, and algorithms as potential sources of competitive advantage (Barney, 1991; Younis et al., 2021), while the Dynamic Capabilities View (DCV) emphasizes firms' ability to sense, seize, and transform using AI (Teece, 2007). For SMEs, however, structural constraints often limit access to such capabilities, potentially reinforcing asymmetries with larger firms.

Sustainability perspectives extend this view through the TBL approach, emphasizing economic, environmental, and social performance (Carter & Rogers, 2008; Seuring & Müller, 2008). Contingency Theory further highlights that the effectiveness of AI adoption depends on contextual factors such as firm size, industry conditions, and institutional environments (Lawrence & Lorsch, 1967). While these perspectives explain adoption and performance, they offer limited insight into developmental outcomes.

2.2 Human Development and Critical Perspectives

To address this limitation, human-centered theories shift attention from performance to capability development. Sen's Capability Approach defines development as the expansion of individuals' substantive freedoms (Sen, 1999), emphasizing capabilities rather than outcomes. Applied to SMEs, this perspective requires evaluating AI in terms of its impact on agency, decision-making autonomy, and access to opportunities (Qureshi, 2023).

Critical perspectives further caution against uncritical adoption. Research on algorithmic bias and data-driven asymmetries shows how AI can reinforce inequalities and constrain autonomy (O'Neil, 2017). Decolonial and postcolonial approaches emphasize the importance of epistemic diversity and context-sensitive solutions, challenging standardized, large-firm-centric models (Sahay et al., 2025). Together, these perspectives raise a key question: does AI enhance SME capabilities, or does it deepen structural dependency?

2.3 Integrative and Process-Oriented Frameworks

Integrative frameworks bridge firm-level and human-centered perspectives. Socio-Technical Systems (STS) theory emphasizes the joint optimization of technological and social elements, highlighting the role of work practices, skills, and organizational context in shaping outcomes (Trist & Bamforth, 1951). The Technology–Organization–Environment + Human (TEO+H) framework further captures how contextual and human factors influence technology use (Cheng & Huang, 2023).

Qureshi's (2023) Cycles of Development framework extends this view by conceptualizing development as dynamic feedback loops between technology, institutions, and human agency. AI can thus trigger virtuous cycles that enhance capabilities or vicious cycles that reinforce constraints. This perspective shifts analysis from static adoption to evolving developmental trajectories.

2.4 Synthesizing the Research Landscape: Identified Gaps and Contribution

Taken together, the literature reveals a multi-layered gap in understanding the developmental implications of AI in SMEs. First, existing research remains largely diagnostic, focusing on adoption drivers and performance outcomes while lacking systematic approaches to assess how AI-enabled processes reshape work practices and influence human and organizational capabilities (assessment void). Second, dominant paradigms emphasize efficiency and optimization without a clear normative foundation, overlooking whether AI expands or constrains agency, learning, and opportunity structures (governance gap). Third, prevailing AI models are designed for large, resource-rich firms, creating a scale mismatch that neglects the structural constraints and contextual realities shaping SME experiences (scale paradox). Collectively, these gaps highlight the absence of context-sensitive, capability-oriented evaluation frameworks that capture the developmental impact of AI beyond performance metrics. Addressing this need, this study develops the concept of DCI and proposes an assessment framework to evaluate how AI-enabled processes influence capability formation in SMEs.

3. RESEARCH METHODOLOGY

This study adopts a Design Science Research (DSR) methodology to develop and refine a DCI assessment framework for evaluating AI-enabled work transformation in SMEs. DSR is appropriate for this study because it supports the development of theoretically grounded and practically relevant evaluative artifacts that address identified gaps in existing literature (Gregor & Hevner, 2013).

3.2 Theoretical Grounding and Construct Development

The DCI framework is derived through an integrative synthesis of four theoretical streams:
Sen's (1999) Capability Approach, which defines development as the expansion of substantive freedoms and emphasizes agency and opportunity; Qureshi's (2023) Cycles of Development, which conceptualizes development as dynamic feedback loops between technology, institutions, and human agency; Socio-Technical Systems (STS) theory, which highlights the joint optimization of technical systems and work practices; TEO+H framework, which emphasizes the role of human and contextual factors in technology adoption and use. Additionally, critical perspectives on AI are incorporated to account for issues of power asymmetry, algorithmic bias, and epistemic limitations in AI systems. This theoretical integration leads to the conceptualization of DCI as a multi-dimensional construct capturing the extent to which AI-enabled processes expand or constrain capabilities in SME contexts.

3.3 Framework Design and Operationalization

In this phase, the DCI construct is translated into an assessment framework comprising multiple dimensions (constructs) of capability development. These constructs are agency expansion, skill development, opportunity expansion, equity impact, and institutional reinforcement. Each dimension is operationalized into observable indicators that reflect AI's impact on work practices, decision-making autonomy, and organizational learning. Table 1 presents DCI model, derived through conceptual mapping of key constructs and measurement items with the literature review.

3.4 Expert Validation

To ensure content validity and theoretical coherence, the preliminary DCI framework is evaluated through expert review. Experts are selected from three domains: artificial intelligence and digital transformation, supply chain management and SMEs, and human-centered development research. The evaluation focuses on clarity of constructs, theoretical alignment, relevance to SME contexts, and completeness of developmental dimensions. Feedback from this stage is used to refine and consolidate the framework structure and indicators.

3.5 Pilot Application and Reliability

The refined framework is subsequently subjected to a pilot application in selected SME contexts where AI-enabled processes are actively used. The pilot assesses the usability, clarity, and practical applicability of the DCI framework, as well as the preliminary consistency of its dimensions.

3.6. Implementation

Findings from the pilot phase are used to iteratively refine the framework, ensuring its relevance and robustness for broader application.

4. CONCLUSION

This study aims to make a key academic contribution by introducing the concept of Developmental Capability Intensity (DCI) and operationalizing it as an assessment framework for evaluating the developmental impact of AI-enabled processes in SMEs. By integrating Sen (1999)'s Capability Approach, Qureshi's (2023) Cycles of Development, and socio-technical perspectives, the study extends existing AI and supply chain literature beyond its dominant focus on efficiency, adoption, and performance outcomes toward a capability-oriented understanding of digital transformation.

From a managerial perspective, the framework provides a structured tool for assessing whether AI investments enhance or constrain critical dimensions such as agency, learning, opportunity expansion, and contextual adaptability, enabling more balanced and developmentally informed decision-making in SMEs.

Future research should empirically validate the DCI framework across different sectors and institutional contexts, refine its measurement scales, and explore longitudinal dynamics of capability development. Further comparative studies between SMEs and larger firms would also help strengthen the theoretical robustness and generalizability of the framework.

REFERENCES

Alghababsheh, M., & Gallear, D. (2022). Social sustainability in the supply chain: a literature review of the adoption, approaches and (un)intended outcomes. Management & Sustainability: An Arab Review, 1(1), 84–109. https://doi.org/10.1108/MSAR-01-2022-0003

Alhasawi, E. A., Hajli, N., & Dennehy, D. (2023). A review of artificial intelligence (AI) and machine learning (ML) for supply chain resilience: Preliminary findings. In 2023 8th International Conference on Smart and Sustainable Technologies (SpliTech). IEEE. https://doi.org/10.1109/ISTAS57930.2023.10306041

Andoh-Baidoo, F. K. (2017). Context-specific theorizing in ICT4D research. Information Technology for Development, 23(2), 195–211. https://doi.org/10.1080/02681102.2017.1356036

Barney, J. B. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99–120. https://doi.org/10.1177/014920639101700108

Carter, C. R., & Rogers, D. S. (2008). A framework of sustainable supply chain management: Moving toward new theory. International Journal of Physical Distribution & Logistics Management, 38(5), 360–387. https://doi.org/10.1108/09600030810882816

Cheng, Y., Li, S., & Huang, F. (2023). A TOE–HOT fit framework for understanding the adoption of digital technologies in organizations. Technology in Society, 75, 102344. https://doi.org/10.1016/j.techsoc.2023.102344

Collins, C., Dennehy, D., Conboy, K., & Mikalef, P. (2021). Artificial intelligence in information systems research: A systematic literature review and research agenda. International Journal of Information Management, 60, 102383. https://doi.org/10.1016/j.ijinfomgt.2021.102383

Dash, R., McMurtrey, M., Rebman, C., & Kar, U. K. (2019). Application of artificial intelligence in automation of supply chain management. Journal of Strategic Innovation and Sustainability, 14(3), 43–52. https://doi.org/10.33423/jsis.v14i3.2105

Gregor, S., & Hevner, A. R. (2013). Positioning and presenting design science research for maximum impact. MIS Quarterly, 37(2), 337–355. https://doi.org/10.25300/MISQ/2013/37.2.01

Guo, W. (2023). Exploring the value of AI technology in optimizing and implementing supply chain data for pharmaceutical companies. Innovation in Science and Technology, 2(3). https://doi.org/10.56397/IST.2023.05.01

Hall, A., & Midgley, J. (2004). Social policy for development. SAGE Publications. https://doi.org/10.1017/S0047279405228805

Kot, S. (2018). Sustainable supply chain management in small and medium enterprises. Sustainability, 10(4), 1143. https://doi.org/10.3390/su10041143

Lawrence, P. R., & Lorsch, J. W. (1967). Organization and environment: Managing differentiation and integration. Harvard Business School Press. https://doi.org/10.2307/2391270

McGrath, K. 2005. Doing critical research in information systems: a case of theory and practice not informing each other, Information Systems Journal (15), pp. 85-101.

OECD. (2024). *Peru's first data-driven pastry shop scales up business operations with digital technologies (Maria Almenara)*. OECD Digital for SMEs Global Initiative.

O'Neil, C. (2017). Weapons of math destruction: How big data increases inequality and threatens democracy. Crown. https://doi.org/10.5860/crl.78.3.16599

Pessot, E., Zangiacomi, A., Marchiori, I., & Fornasiero, R. (2023). Empowering supply chains with Industry 4.0 technologies to face megatrends. Journal of Business Logistics, 44(4), 609–640. https://doi.org/10.1111/jbl.12360

Qureshi, S. (2023). Cycles of development in systems of survival with artificial intelligence: A formative research agenda. Information Technology for Development, 29(2-3), 171–183. https://doi.org/10.1080/02681102.2023.2236424

Qureshi, S., Nadendla, K., & Oladokun, B. (2024). Digital innovations for development: Design of artificial intelligence in mobile health. Thirtieth Americas Conference on Information Systems, Salt Lake City.

Sahay, S., Srivastava, S. C., Barrett, M., Davison, R. M., Madon, S., Schlagwein, D., Brown, I., & Sarker, S. (2025). Digital development: Reimagining research beyond ICT4D. Information Systems Research. Advance online publication. https://doi.org/10.1287/isre.2025.editorial.v36.n3

Sen, A. (1999). Development as freedom. Oxford University Press. https://doi.org/10.1093/ije/30.4.907-a

Seuring, S., & Müller, M. (2008). From a literature review to a conceptual framework for sustainable supply chain management. Journal of Cleaner Production, 16(15), 1699–1710. https://doi.org/10.1016/j.jclepro.2008.04.020

Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. Strategic Management Journal, 28(13), 1319–1350. https://doi.org/10.1002/smj.640

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. https://doi.org/10.1177/001872675100400101

Tukamuhabwa, B. R., Stevenson, M., Busby, J., & Zorzini, M. (2015). Supply chain resilience: Definition, review and theoretical foundations for further study. International Journal of Production Research, 53(22), 5592–5623. https://doi.org/10.1080/00207543.2015.1037934

Younis, H., Alsharairi, M., & Sundarakani, B. (2021). Applications of artificial intelligence and machine learning within supply chains: Systematic review and future research directions. Journal of Modelling in Management. Advance online publication. https://doi.org/10.1108/JM2-12-2020-0322

APPENDIX

Table 1: Developmental Capability Index (DCI) for Assessing AI-Enabled Work Transformation in SMEs

DCI Dimensions (constructs)	Indicators	Guiding developmental question	Low DCI means	High DCI means	Related Studies
1 - Agency Expansion - AE Agency Expansion in DCI is concerned not with whether humans can act in a given moment, but with whether AI use expands what humans are able to become and do in the future, such as solving more complex problems even beyond the support of the AI system	AE1-Strategic Initiative	*Do actors initiate new directions over time?*	AI helps me execute assigned tasks but does not influence strategic choices	AI helps me identify and pursue new strategic opportunities.	Teece (2007) -
	AE2-Role Expansion & Autonomy	*Do human roles evolve or narrow?*	My role has become more limited since AI adoption	AI use has expanded my responsibilities and decision scope	Qureshi et al. (2024) Teece (2007)
	AE3-Control Over Future Options	*Are future choices expanded or constrained?*	Using AI has reduced my ability to change how I work	AI use has increased my long-term strategic flexibility	Amartya Sen (1990, 1999) Mthoko & Khene (2018)
	AE4-Self-Directed Capability Accumulation	*Is agency cumulative and self-reinforcing?*	AI does not contribute to my long-term skill development	AI helps me build capabilities that I can use independently	Mthoko & Khene (2018) Teece (2007) Evans (2014)

DCI Dimensions (constructs)	Indicators	Guiding developmental question	Low DCI means	High DCI means	Related Studies
2 - Skill Development-SD Whether AI adoption contributes to the long-term expansion of human capabilities or is it merely substitutes for them. The focus is not short-term productivity, but whether people emerge more capable after sustained AI use.	SD1-Capability Accumulation	*Do human skills increase over time?*	My skill level does not improve after the initial use of the AI system	My skills continue to improve as I work with the AI system	Evans (2014) in Roberts et al. (2015) Teece (2007) - Mthoko & Khene (2018)
	SD2-Transferability of Skills	*Are capabilities portable beyond the AI system?*	What I learn from this AI system is not useful outside this tool	The skills I gain can be applied to other tools or contexts	Amartya Sen (1990) - Evans (2014):
	SD3-Human Judgment Development	*Does AI strengthen or weaken expertise?*	I rely on the AI's judgment rather than my own	Using the AI helps me develop stronger independent judgment	Qureshi (2023) - "Trist & Bamforth (1951)
	SD4-Learning Infrastructure & Continuity	*Is skill formation embedded institutionally?*	There is little support for continued learning after adopting the AI.	Ongoing learning and skill development are actively supported	Teece (2007): Evans (2014): Mthoko & Khene (2018):

DCI Dimensions (constructs)	**Indicators**	**Guiding developmental question**	**Low DCI means**	**High DCI means**	**Related Studies**
3 - Opportunity Expansion- OE Opportunity Expansion examines whether AI adoption broadens access to new markets, resources, roles, and developmental pathways — or instead reinforces existing constraints.	OE1-Market Access Expansion	*Does AI enable entry into new markets or customer segments?*	AI use does not expand access to new markets or customers	AI enables access to markets or clients that were previously unreachable	Qureshi (2023) Teece (2007)
	OE-2Resource Access Expansion	*Does AI expand access to critical data, infrastructure, or capital?*	AI adoption increases dependence on externally controlled resources	AI adoption improves access to critical data or infrastructure	Qureshi et al. (2024) Evans (2014) in Roberts et al. Mthoko & Khene (2018)
	OE3-Role & Pathway Diversification	*Does AI create new professional roles or developmental pathways?*	AI has not created new professional opportunities	AI has enabled new roles or career pathways	Qureshi (2023): Mthoko & Khene (2018): Sen (1990)
	OE4-Strategic Option Expansion	*Does AI increase long-term strategic flexibility and choice?*	AI adoption limits our strategic flexibility	AI adoption expands our strategic options for future growth	Teece (2007): Mthoko & Khene (2018)

DCI Dimensions (constructs)	**Indicators**	**Guiding developmental question**	**Low DCI means**	**High DCI means**	**Related Studies**
4 - Equity Impact- EI Equity Impact examines whether AI adoption reduces structural inequalities and power asymmetries — or whether it reinforces and deepens them over time.	EI1- Distribution of Benefits	*Are AI-enabled gains shared broadly or concentrated among advantaged actors?*	The benefits of AI primarily accrue to already well-resourced actors	AI benefits are distributed across different levels of actors or organizations	Qureshi (2023) Evans (2014) in Roberts et al. - "Qureshi et al. (2024)
	EI2-Power Asymmetry Dynamics	*Does AI reduce or reinforce structural power imbalances?*	AI adoption increases dependence on dominant platforms or actors	AI adoption strengthens the bargaining position of smaller or local actors	Qureshi (2023):. Andoh-Baidoo (2017) -.
	EI3-Access to Capability Development	*Are opportunities for learning and skill-building inclusive?*	Access to AI-related training is limited to a select group	Opportunities to build AI-related capabilities are widely accessible	Evans (2014): Mthoko & Khene (2018) -
	EI4-Long-Term Structural Impact	*Does AI contribute to reducing persistent inequalities over time?*	AI adoption reinforces existing structural inequalities	AI adoption contributes to reducing long-term structural inequalities	Qureshi (2023): Mthoko & Khene (2018). Amartya Sen (1990/1999)

DCI Dimensions (constructs)	**Indicators**	**Guiding developmental question**	**Low DCI means**	**High DCI means**	**Related Studies**
5 - Institutional Reinforcement-IR Whether AI adoption strengthens the institutions, coordination mechanisms, and collective capacities that sustain long-term human development.	IR1- Governance & Rule-Setting	*Are institutions able to govern AI use effectively?*	Rules governing AI use are unclear or determined outside our institution.	Our institution actively defines and revises rules governing AI use	Qureshi et al. (2024) - Qureshi (2023) Slaughter (2004) in Roberts et al..
	IR2- Coordination & Collective Capacity	*Does AI enable collaboration across actors?*	AI systems are used independently with little coordination across units or organizations	AI use improves collaboration and shared capacity across actors	Teece (2007) Keck & Sikkink (1998) in Roberts et al. "Qureshi (2023)
	IR3- Institutional Resilience & Continuity	*Are institutions more robust over time?*	If the AI system were removed, our institution would lose critical capabilities	Our institution can adapt or replace AI systems without losing core capabilities	Evans (2014) in Roberts et al. Mthoko & Khene (2018)
	IE4-Inclusion & Developmental Spillovers	*Do benefits extend beyond primary users?*	Only a small group benefits from AI-enabled capabilities	AI-enabled capabilities spill over to broader groups beyond primary users	Qureshi (2023): Andoh-Baidoo (2017) Chorev (2012) in Roberts et al.