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Artificial Intelligence-Driven Digital Transformation and Sustainable Innovation in Pharmaceutical Firms: The Mediating Role of Knowledge Management Capability

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Abstract
The landscape of pharmaceutical discovery, manufacturing, quality, regulatory and commercial decision-making is transforming due to AI (artificial intelligence). How can evidence be provided that AI can be leveraged to improve individual tasks and then become an organisational capability for sustainable innovation? This study proposes an "AI–Knowledge Capability Conversion (AI-KCC)" framework with a focus on knowledge management capability as the pivot in the AI-driven digital transformation process, and the connection between the digital transformation and environmental, economic and social innovation. The introduction of the concept of dynamic capabilities theory and the knowledge-based view and the resource-based view of the firm intends to highlight the difference between technological potential and value creation as it is possible through capabilities and digital leadership is introduced as a boundary condition. The survey data was gathered from 486 key informants (KIs) (managerial and professional level) from each pharmaceutical company in India and was analysed with the partial least squares structural equation modelling (PLS-SEM). The use of AI for DT is positively correlated with the knowledge management capability and sustainable innovation. The impact of knowledge management capability is direct and strong on sustainable innovation and it has a partial mediation effect on the focal relationship. Digital leadership boosts the pathway from transformation-to-knowledge and yields a greater conditional indirect effect. The model shows good reliability, validity and predictive relevance from the perspective of explaining 52.1% of the variance in the knowledge management capability and 64.3% in sustainable innovation. The study theorises the value of AI as an information-generating infrastructure and identifies four routines (acquisition, sharing, integration and application) as being critical in achieving this value. It, therefore, broadens the scope of pharmaceutical AI research from implementation and improvement of processes to organisational transformation processes that lead to lasting innovations.

Keywords: *artificial intelligence; digital transformation; knowledge management; sustainable innovation; pharmaceuticals; PLS-SEM*

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I. Introduction

AI has gained strategic value in all areas of the pharmaceutical industry from discovery through clinical development, manufacturing, pharmacovigilance and regulatory. Search, prediction and classification (Arden et al., 2021; Harrer et al., 2019; Mak & Pichika, 2019; Paul et al., 2021; Vamathevan et al., 2019) process visibility and coordination can be achieved with the help of machine learning. Examples of technical possibilities include studies of molecule creation (Fleming, 2018), discovery of antibiotics (Schneider et al., 2020), computer-assisted drug design (Stokes et al., 2020) and the creation of molecules (Zhavoronkov et al., 2019). However, high performance at tasks is not enough to ensure that AI will prove to be a sustained organisational innovation.

In particular this is true in the pharmaceutical industry. The transfer of information between the scientific, engineering, quality, regulatory and commercial fields and decisions must be justified, recorded and verified. An algorithm may well generate the right molecule, it may generate the right signal for safety, it may generate something about the process that is abnormal, but it is only when an employee can interpret that output, relate that output to domain knowledge, share it across functions, and put that in controlled action, that value can be realised. AI is thus not a capability that is self-executing in the organisation, but rather has informational potential. Different results can be achieved with similar technologies because of variations in data assets and

practices of the companies, learning routines (Jöhnk et al., 2021; Mikalef & Gupta, 2021), leadership and governance (Canhoto & Clear, 2020; Raisch & Krakowski, 2021).

Three gaps follow. First, there is a prevailing paradigm in pharmaceutical AI research that is still technology and use-case-oriented, and second, there is a beginning shift towards the study of digital transformation as a phenomenon of the organisation and management of the firm, as highlighted in the work of Bate & Hobbiger (2021), Fröling et al. (2024), and Miozza et al. (2024). Second, the wider digital transformation studies show that other capabilities of the organisation (apart from knowledge management) complement the value of digital transformation. (Borges et al., 2021; Gupta & George, 2016; Mikalef et al., 2020; Wamba et al., 2017). Third, the outcome of the innovation is usually operational or financial, but if it is to be sustainable, it must have environmental, economic and social value, which is realised simultaneously (Bai et al., 2020; Calik & Badurdeen, 2016; Klewitz & Hansen, 2014; Adams et al., 2016).

Table 1. Research positioning and contribution

Stream	Established insight	Gap addressed
Pharmaceutical AI	AI improves discovery, manufacturing, safety and information work.	Explains how task-level outputs become organisational sustainable innovation.
Digital transformation	Digital technologies reshape strategy, processes and ecosystems.	Specifies KMC as the conversion mechanism rather than assuming a direct effect.
Knowledge management	Knowledge processes support innovation and performance.	Positions acquisition, sharing, integration and application as a focal mediator.
Sustainable innovation	Capabilities support environmental and economic renewal.	Integrates environmental, economic and social innovation in one outcome.
DCT, KBV and RBV	Sensing, knowledge integration and resource bundles explain advantage.	Combines the theories in an observable AI-KCC causal sequence.
Digital leadership	Leadership supports readiness and change.	Tests first-stage moderation and conditional mediation.

This paper aims to fill these gaps, by modelling AI-driven digital transformation (AIDT) as the independent variable, knowledge management capability (KMC) as the mediator and sustainable innovation (SI) as the outcome variable. Digital leadership (DL) is a moderator between AIDT–KMC relationship. The theory is based on the concepts of dynamic capabilities, knowledge-based view (KBV) and resource-based view (RBV). AIDT increases sensing and analysis capability; KMC transforms digital information into a shared and made applicable knowledge; and embedded conversion routines help build a capability bundle that is specific to a firm and can be used to reconfigure its resources (Barney, 1991; Grant, 1996; Teece, 2007; Teece et al., 1997).

The study makes a contribution with an AI–Knowledge Capability Conversion framework. It differentiates between information generation and organisational knowing, defines the mediation effect, adds leadership as a boundary condition and outlines sustainable innovation as a result of reconfiguring knowledge using digital means. The data also contains studies from Indian pharmaceutical companies to enable research outside the advanced economies where the majority of research on organisational AI takes place.

The research problem is narrower in the context of the emerging economy. Pharma companies can possess great scientific and manufacturing expertise, but have different data architectures, lack hybrid digital-domain expertise and depend on external technology providers. This is because these are not the only reasons to consider adoption a sign of transformation. Without the routines to challenge outputs, share learning around the world, or incorporate sustainability into investment and product decisions, a company can obtain a common platform without it. The Indian context in this way is the theoretical context other than geographical context in the capability conversion process.

II. Theoretical background

2.1 AI-driven digital transformation

Digital transformation is a process of change in which digital technologies impact not just on the digitisation of existing records, but on the way the organisation operates, its strategy, processes, structures and relationships (Bharadwaj et al., 2013; Verhoef et al., 2021; Vial, 2019). Digital technologies are generative and (re-)programmable, as they offer possibilities for innovation through recombination across domains (Nambisan et al., 2017; Yoo et al., 2010). Assimilation of AI in the relevant tasks, data integration, process reconfiguration and connectivity with external partners are four interrelated aspects of AIDT. This definition differentiates the strategic transformation from the purchase of an individual product.

Pharmaceutical AI's potential to improve target identification, design clinical trials, manufacturing control, information retrieval, and safety monitoring can improve efficiency and streamline research and development. In Industry 4.0, these applications are developed with the help of sensors, automation systems and real-time quality systems (Arden et al., 2021; Bate & Hobbiger, 2021). But, adopting the model does not ensure its accuracy, transfer and accountability in use. There are some tasks which can be automated via AI, but more

professional interpretation and coordination is needed which forms an automation–augmentation paradox (Raisch & Krakowski, 2021). Complementary routines and resources are therefore essential for the added value of the organisation (Haefner et al., 2021; Wamba-Taguimdje et al., 2020) because they can be seen as complementary resources to the organisation.

2.2 Knowledge management capability

The KBV (Grant, 1996; Kogut & Zander, 1992) views firms as institutions which serve to integrate specialised knowledge. Organisational knowledge is only knowledge when meaning is added to the data, reliability is assessed, conclusions are drawn, and actions are taken. Thus, the acquisition, sharing, integration and application of KMC can be defined. However, the impact of capability is also influenced by trust, incentives, and common language and managerial coordination (Alavi & Leidner, 2001; Gold et al., 2001; Lee & Choi, 2003) that are enabled through the use of technical infrastructures.

Some research has already been done to link knowledge processes, innovation and performance. The steps included in the search process (such as seeking input from other experts in acquisition), the interpretation process (such as reconciling differing views), and the application process (such as changing decisions and routines) (Andreeva & Kianto, 2012; Darroch, 2005; Wang & Wang, 2012). Influenced by organisational learning (OL), human resource practices (HRP) and knowledge-oriented leadership (KOL) (Chen & Huang, 2009; Donate & de Pablo, 2015; Jerez-Gómez et al., 2005; Jiménez-Jiménez & Sanz-Valle, 2011). In the context of artificial intelligence KMC must be able to integrate the codes generated by the machine with the tacit domain knowledge. Relevance of application of knowledge is especially crucial as knowledge that is not shared in dashboards or teams of experts will not have an impact towards sustainable innovation (Manesh et al., 2021; Ode & Ayavoo, 2020).

2.3 Sustainable innovation

Sustainable innovation involves the development of a product, process or organisational practice that delivers economic benefits and does not cause environmental harm and improves the social outcomes (Adams et al., 2016). Lower energy, material use, waste and risk are all aspects of environmental innovation. Economic innovation is productivity, resilience, quality and commercially viable products and services. Social innovation is everything from safety, access, etc. to the ability of staff, and the value of stakeholders. They are all factors that need to be considered together: It may be a technically 'green' solution, but socially 'excluded' and economically 'fragile'.

Regulation, technological opportunity/demand and organisational capability (Horbach et al., 2012; Rennings, 2000) are all factors that affect eco-innovation. The introduction of green competence may be advantageous to gain benefits; conversely, the introduction of Industry 4.0 may help to monitor, trace and orchestrate resources (Chen, 2008; Ghobakhloo, 2020; Kamble et al., 2018). However, digitalisation is not sustainable in itself. Benefits will depend on the objectives, as well as governance and rebound effects (Bai et al., 2020; de Sousa Jabbour et al., 2018; Vinuesa et al., 2020). The Knowledge Management Capability (KMC) offers a way to incorporate scientific, process, supplier, regulatory and stakeholder knowledge on these trade-offs.

2.4 Integrated theoretical logic

Dynamic capabilities theory can be used to understand the mechanisms of sensing, seizing and transforming in the context of change. AIDT takes the analysis beyond the limits of the traditional kind, and speeds up that analysis, but to be shared interpretations of signals, the resources have to be. The KBV offers a description of this conversion via knowledge integration & application. Path- and organisation-dependent and hard to replicate data, knowledge, governance, trust, and learning are captured in the RBV, as are vendor-bundled AI products, which are spread out. KMC makes a popular digital tool into an integral part of an organisation. (Eisenhardt & Martin, 2000).

Digital leadership is a condition for activation. Leaders establish agendas, focus attention, connect technical and domain knowledge, give room for experimentation, make decisions that lead to accountability. They are the decision-makers on whether AI-powered information goes into the organisation's learning, or stays as a separate entity. The following reasoning leads to the conceptual model, presented in Figure 1.

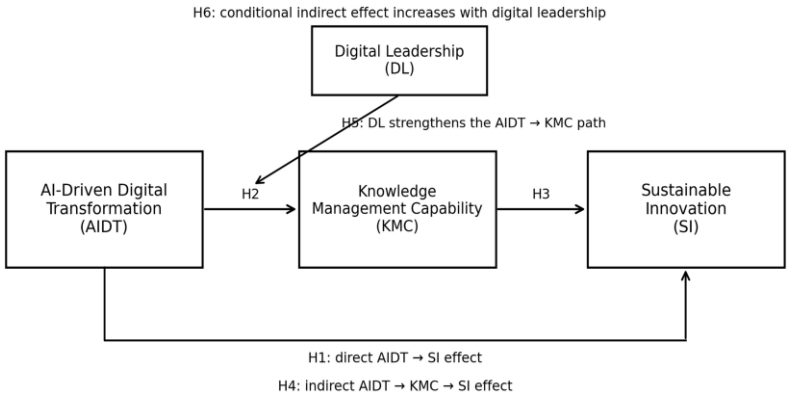

Figure 1. The hypotheses along with a conceptual model.

2.5 AI–Knowledge Capability Conversion framework

The AI-KCC framework takes the view that value creation can be broken down into four steps. Digital sensing produces (virtual) representations using data which characterise the (scientific, operational and external) situation. Second, in knowledge conversion, these representations go through acquisition, sharing, integration and application processes. Thirdly, reshape resources, redefine decision rights, redefine asset usage and inter-organisational relationships. Fourth, the results of these changes are environmental, economic and social innovations. Stages are easily separable with analysis. High sensing can be combined with low conversion, and high conversion can be set up for high efficiency without any sustainability considerations. It is therefore essential that SI be both conversion-oriented and have an outcome orientation.

This sequence also helps to make clear the functions of three theories. The temporal logic of sensing and transformation is given by the dynamic capabilities theory. The KBV is one of the important organisational challenges to integrate specialist knowledge. The RBV can also provide an understanding of the conditions that can create this heterogeneity even if competitors have access to AI tools, like conversion routines. The theories do not provide an alternative option for each other. The lack of KBV in dynamic capabilities leaves the transition in the informational stock not completely specified; the lack of dynamic capabilities in KBV does not tell much about the renewal in the context of a fast-changing technology. The process model AI-KCC accompanies them in their trip to strategic value of a digital resource: it is path-dependent.

Leadership is represented in the first conversion stage, where it is directly involved with the development of transformation infrastructure to become organisational learning; the leadership of DL runs across the sequence. Leaders' decisions about what is listened to, who is listening to it, and how disagreements are taken care of and responsibilities shared will make a difference in signals that are attended to. They also give a definition of reasonable mistakes, validation and accountability. These actions influence the outcomes of KMC prior to choosing any particular sustainable outcome. Modelling DL as the first-stage moderator, therefore, is a valid assumption as it makes a more accurate assertion than assuming that leadership is an additional direct antecedent of innovation.

III. Hypothesis development

AIDT can contribute to SI in various ways, including: quicker experimentation, improved resource transparency, real-time optimisation and improved ecosystem coordination. Embedded digital resources (Gupta & George, 2016; Mikalef et al., 2020; Wamba et al., 2017) have the potential to improve innovation and performance of the analytics capabilities. Pharmaceutical digitalisation is not only changing the innovation architectures, but also the architecture of innovation itself (Mariani et al., 2023; Miozza et al., 2024). Thus:

H1: According to the results, there is a positive relationship between AI and sustainable innovation in the context of digital transformation.

There is also an increase in the quantity, quality and accessibility of information with AIDT. New platforms and new ways of working involve feedback loops of reviewing the output, discussing exceptions and keeping lessons. These mechanisms validate acquisition, sharing, integration and application – unless transformation is bound to specialist projects they validate these processes.

H2: AI usage is positively related with digital transformation and digital transformation is correlated with the capability of knowledge management.

The elements of technical, commercial, environmental and stakeholder knowledge are all needed for SI. KMC helps to facilitate the recombination of ideas, reduce duplication and transfer of learning between tasks. This

results in higher quality and faster rate of innovation (Darroch, 2005; Jiménez-Jiménez & Sanz-Valle, 2011; Ode & Ayavoo, 2020) when it comes to organisational learning and application of knowledge.

H3: This study shows that sustainable innovation is positively related to the knowledge management capability.

The basic argument of mediation. The majority of AI products are categorisations, predictions, suggestions and digital representations. The acquisition routines identify the outputs of relevance, the sharing process makes them the focus of the professionals' attention, the integration process relates algorithmic and experiential knowledge, and the application process translates the outputs validated into action in the domain of decision. This series is designed to combine the digital sensing and reconfiguration of resources, and emphasise that technology is only a part of the answer (Nonaka, 1994; Pavlou & El Sawy, 2011; Zollo & Winter, 2002).

H4: Therefore, AIDT has indirect influence on SI through KMC and strengthening leadership in AIDT should be considered as a way to strengthen the indirect influence of AIDT on SI through KMC.

Digital leadership must continue along the AIDT–KMC journey and boost its visibility, define ownership for digital leadership, provide cross-functional challenges and link experimentation with governance. The research on AI readiness and digital capability (Helfat & Raubitschek, 2018; Jöhnk et al., 2021; Warner & Wäger, 2019) shows that the conditions of the organisation are fundamental for AI readiness and digital capability, which include leadership, strategic alignment and change capacity.

H5: AI-driven digital transformation and knowledge management capability will be positively moderated by digital leadership.

H6: AI-enabled digital transformation's impact on sustainable innovation via knowledge management capability is greater with the higher digital leadership level.

IV. Method

4.1 Setting, sample and procedure

The cross-sectional survey was carried out with the Indian pharmaceutical companies' managers and professionals. Those who were eligible could have been in an organisation for at least two years, knowledgeable of a key digital project, and involved in R&D, manufacturing, quality, regulatory affairs, digital/IT, strategy, sustainability or supply. Printed directories and a number of industry networks were used to build a sampling frame and one key informant was retained per company. 1,240 individually addressed questionnaires were distributed, that is, 532 questionnaires. After excluding answers with missing data, answers that were patterned with similar answers and cases that did not include answers to the attention checks, 486 firm-level responses were usable, of which 39.2% (486) were deemed effective responses. The study was done with voluntary participation, informed consent and no personally identifying information was collected.

Table 2. Sample profile (486 key informants representing 486 firms)

Characteristic	Main categories	Distribution
Function	R&D/innovation; manufacturing; quality/regulatory; digital/IT; other	27.0%; 22.6%; 18.5%; 14.8%; 17.1%
Level	Senior; middle; specialist	31.7%; 43.2%; 25.1%
Firm size	<250; 250–999; ≥1,000 employees	28.0%; 32.3%; 39.7%
Ownership	Indian private; multinational; other	59.1%; 23.0%; 17.9%

The common method risk was reduced using procedural remedies. Neutral instructions between predictor and criterion blocks and all efforts were made to emphasise the importance of confidentiality and to intersperse the items. The proposed causal ordering was not told to the respondents. All of the supplementary diagnostics and full collinearity VIFs were within the range of 1.68 to 2.74, with the first unrotated factor accounting for 34.7% of the variance. Podsakoff et al. (2003) and Kock (2015) found neither of these diagnostic methods explained the observed relationships.

4.2 Measures

All constructs were adapted from and then customised to use on seven-point agreement scales from literature. The item relevance and clarity were examined by four academics and six pharmaceutical managers followed by a pilot of 38 respondents. AIDT was found to be a reflective-formative higher-order construct that was evaluated using 15 items pertaining to assimilation of AI, data integration, process reconfiguration and ecosystem connectivity. KMC was used as a reflective–formative higher-order construct reflecting its measurement by 16 items related to knowledge acquisition, sharing, integration and application. SI was a reflective–formative higher-order construct that was measured using 12 items, which cover environmental, economic and social innovation. DL is a first-order construct that was developed from six items that are related to digital vision, digital empowerment, mobilisation and responsible governance. Firm size, age, ownership, and R&D intensity and respondent tenure were used as controls.

Table 3. Construct operationalisation

Construct	Operationalisation	Principal scale foundations
AIDT	15 items across AI assimilation, data integration, process reconfiguration and ecosystem connectivity.	Gupta & George (2016); Mikalef & Gupta (2021); Verhoef et al. (2021)
KMC	16 items across knowledge acquisition, sharing, integration and application.	Gold et al. (2001); Lee & Choi (2003); Ode & Ayavoo (2020)
SI	12 items across environmental, economic and social innovation.	Adams et al. (2016); Calik & Badurdeen (2016); Chen (2008)
DL	Six reflective items covering digital vision, empowerment, mobilisation and responsible governance.	Donate & de Pablo (2015); Jöhnk et al. (2021); Warner & Wäger (2019)

4.3 Analysis

Due to the emphasis of the model on prediction and theory extension it has been decided to use the software SmartPLS 4, as this software is suitable to handle higher-order composites and estimate interaction and conditional indirect effects. A two-stage approach with scores for the first-order model estimated first, followed by the higher-order model was used. Alpha, rho_A and composite reliability were used to test the reliability; average variance extracted was used to test the convergent validity; and HTMT (Fornell & Larcker, 1981; Henseler et al., 2015) was used to test the construct validity. Standardisation was done on the predictor and moderator before the two-stage interaction term was calculated. In 10,000 bootstrap samples (Nitzl et al., 2016) indirect effects and paths were tested. Two sets of conditional effects were calculated at the mean level and at one SD above and below the mean for DL. There was an in-sample predictive relevance assessment done by blindfolding and an out-of-sample assessment was done by ten-fold PLSpredict (Shmueli et al., 2019). (Hair et al., 2019; Sarstedt et al., 2019).

4.4 Construct specification

Construct specification was developed from dimensions to higher-order concepts, direction of causality. This means that the first-order dimensions were reflective as the items in these dimensions were manifestations of a common dimension. The higher-order constructs were formative, as the dimensions were non-interchangeable components: That is, strong AI assimilation does not offset the lack of data integration, and environmental innovation does not replace and overturn the social innovation. This separation minimises the chances of having expectations for consistency within the different pieces of capability elements.

To check for non-response bias, mean scores for the constructs and the size of the firms and organisational level were compared between early and late responders and there were no significant differences. A key-informant competency check was performed to confirm the competency of each respondent: the respondent's time in role, functional position and direct involvement in a digital initiative. The signs, magnitudes and significance of the focal paths did not change when the lowest 10% of the involvement scores were dropped and the model was re-estimated. All controls were added as blocks and SEs were bootstrapped. These checks do not preclude the possibility of selection and/or endogeneity problems, but reduce the likelihood of getting results from a specific occupational group, firm category and/or specific estimation choice.

The focus of the analysis was on the size of the effects and predictive performance and not only on the significance of the effects. Small coefficients can be large enough in a large sample to achieve conventional thresholds, but do not have strategic significance. These were thus taken as the indirect effect and variance accounted for, and conditional slopes. It was not just about whether the path is different to the zero path, but whether knowledge conversion is a substantial part of the return on innovation and whether the return on innovation is impacted by leadership.

V. Results

5.1 Measurement model

The loadings of the indicators were ≥ 0.708. Alpha ranged from 0.812 to 0.914, rho_A from 0.828 to 0.918, composite reliability from 0.881 to 0.936 and average variance extracted from 0.649 to 0.785. The scores of HTMT were lower than 0.85. All dimension weights were positive and significant and the higher-order outer VIFs were between 1.88 and 2.83.

Table 4. Measurement model summary

Construct/dimension	Loading range	α	rho_A	CR	AVE
AI assimilation	0.742–0.878	0.872	0.879	0.913	0.724
Data integration	0.751–0.891	0.884	0.891	0.921	0.745
Process reconfiguration	0.728–0.866	0.852	0.861	0.900	0.693
Ecosystem connectivity	0.759–0.881	0.812	0.828	0.889	0.728
Knowledge acquisition	0.724–0.867	0.846	0.852	0.897	0.686

Knowledge sharing	0.731–0.892	0.873	0.880	0.914	0.726
Knowledge integration	0.754–0.906	0.897	0.902	0.929	0.766
Knowledge application	0.779–0.918	0.914	0.918	0.936	0.785
Environmental innovation	0.708–0.856	0.821	0.829	0.881	0.649
Economic innovation	0.736–0.879	0.858	0.866	0.904	0.703
Social innovation	0.719–0.861	0.834	0.842	0.890	0.669
Digital leadership	0.748–0.884	0.889	0.895	0.919	0.695

Table 5. Higher-order weights and discriminant validity

Construct	Specification / weight range	Outer-VIF range	Highest HTMT
AIDT	Reflective–formative / 0.221–0.316	1.89–2.83	0.78
KMC	Reflective–formative / 0.214–0.334	1.97–2.63	0.82
SI	Reflective–formative / 0.327–0.356	1.88–2.31	0.76
DL	Reflective first-order / not applicable	Not applicable	0.74

5.2 Structural model

AIDT positively predicted SI (β = 0.241, p < .001) and KMC (β = 0.631, p < .001), supporting H1 and H2. KMC positively predicted SI (β = 0.492, p < .001), supporting H3. The indirect effect AIDT → KMC → SI was 0.310 with a 95% bootstrap confidence interval [0.251, 0.376] which supported H4. The direct effect was complementary and partial since there was still an effect. The total effect was made up of 56.3% indirect effect.

Table 6. Structural model and hypothesis tests

H	Path	β	t	p	95% CI	Decision
H1	AIDT → SI	0.241	4.91	< .001	[0.145, 0.336]	Supported
H2	AIDT → KMC	0.631	15.37	< .001	[0.548, 0.708]	Supported
H3	KMC → SI	0.492	9.84	< .001	[0.391, 0.588]	Supported
H4	AIDT → KMC → SI	0.310	9.69	< .001	[0.251, 0.376]	Supported
—	DL → KMC	0.214	4.32	< .001	[0.118, 0.307]	Constitutive path
H5	AIDT × DL → KMC	0.129	2.98	.003	[0.044, 0.211]	Supported
H6	Index of moderated mediation	0.063	2.63	.009	[0.019, 0.111]	Supported

The main effect of the constitutive DL was positive (β = 0.214, p < .001). This support for H5 is found in the positive prediction of the interaction of AIDT × DL (β = 0.129, p = .003). The slope of the AIDT–KMC was greater at one standard deviation above the mean, 0.760, than it was at one standard deviation below the mean, 0.502; and 0.631 at the mean of DL. The conditional indirect effects were: 0.247, 0.310 and 0.374. The moderated mediation index was 0.063 (non-zero), thus would support H6.

Table 7. Conditional indirect and predictive results

Assessment	Low DL (−1 SD)	Mean DL	High DL (+1 SD) / result
AIDT → KMC slope	0.502	0.631	0.760
Conditional indirect effect	0.247	0.310	0.374
95% CI	[0.190, 0.310]	[0.251, 0.376]	[0.292, 0.460]
R^2 / model fit	KMC = 0.521	SI = 0.643	SRMR = 0.059
Q^2 / PLSpredict	KMC = 0.370	SI = 0.430	6/7 higher-order indicators beat the LM benchmark

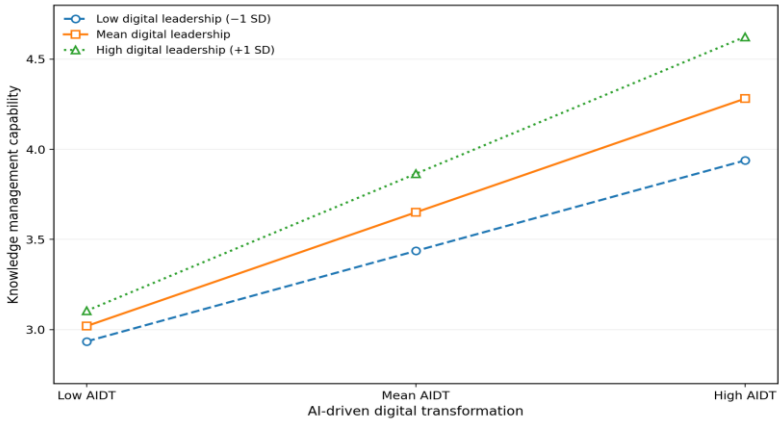

Figure 2. AIDT–KMC is moderated by digital leadership.

For KMC, the model accounted for 52.1% of the variance and for SI, it accounted for 64.3%. Q^2 values were 0.370 and 0.430, respectively. The PLSpredict errors were smaller than the errors using the linear model

for six of the seven endogenous higher-order indicators. No significant differences were produced by adding controls in blocks to the focal coefficients. The other specification options that were combined with the first one, or the other order (mediator – outcome, or outcome – mediator) showed less predictive or explanatory power.

VI. Discussion

The relationship with the KMC is also strong, which will help to understand the meaning of meaningful transformation. The construct also goes beyond the use of tools, but rather encompasses data integration and process reconfiguration as well. Knowledge capability is more likely to emerge when algorithms are coupled with a new workflow and common evidence and feedback loops. In line with the research on digital transformation, it was highlighted that organisation change is an important aspect, rather than digitisation (Bharadwaj et al., 2013; Vial, 2019).

KMC strongly predicts SI since sustainability issues need to be integrated through the boundaries of professionals and stakeholders. An optimisation in manufacturing can lower the amount of material used, but can affect robustness; a digital health service can increase access, but can have privacy and/or exclusion issues. The sharing of knowledge shows its trade-offs, the gathering of the parties can lead to the integration of the conflicting knowledge, and the use of the negotiated knowledge transforms it into practice. It is clear from the dimension weights for balancing the environmental, economic and social benefits of the process that the mechanism is not limited to the efficiency of the process in the green sense.

Digital leadership is one of the facilitators of the conversion process. Leaders foster a curiosity and power to question algorithms, accepted practice. They bring together technical experts and domain experts and help to ensure that validation and governance does not slow down learning, but actually advance it. The substantive interest of the small interaction term is that it means that the return to innovation will be different for the same transformation base.

The results also help to resolve the apparent conflicting perspectives on AI. From another point of view, AI is a technology that can be applied to different sectors, such as search, prediction and automation. Another warns of the loss of value if the produced output by AI is not well communicated, misinterpreted or used in an inappropriate process. AI-KCC accommodates both. As in the other direct path to SI, the mediation path has a much larger component, and organisational conversion plays a critical role in the value of the AIDT, which also offers authentic analytical and coordinating services. The framework does not thus depend on a technological optimism or a social explanation, one that does not attribute computational capabilities.

A focus on knowledge application in KMC needs to be addressed. Acquisition and sharing are requirements and can be seen but does not lead to any change in outcomes. The decision does not get influenced as the firms can establish communities of practice, populate repositories or construct a dashboard. Application is where knowledge is transformed into portfolio decisions, process parameters, standard procedures, design needs and/or stakeholder interventions. It has a relatively robust weight, indicates an action perspective on knowledge capability and recommends further research to differentiate between the actual presence of knowledge practices and their impact on consequential routines.

The partial mediation result also suggests that there are other pathways, aside from KMC. Automated control can bring direct benefits through quicker experiments, and lower coordination costs. Other mediators could be the digital operational capability, absorptive capacity, innovation capability and organisational agility. The "theory" of KMC is not one of exclusivity, but one of a very important pathway, especially one that is important in a transprofessional knowledge environment where evidential requirements must be fulfilled. This can be continued by adding additional mediators, as additional transformations, but not necessarily as additional capabilities.

The moderation pattern suggests in some cases there is no premium on leadership, but a capability multiplier. The best strategic sense of DL is when there is a substantive transformation base. With no data, weak models and fragmented systems, vision and empowerment is not sufficient. However, if the programme is well developed and full of technical detail it can have little impact if management does not establish a good cross-functional ownership and accountable learning environment. The interaction between the technical and managerial aspects in digital transformation then makes it clear that the amount of investment is not a good indicator of innovation.

VII. Theoretical contributions

The AI-KCC framework has four contributions. The first is that it separates out from organisational knowing the algorithmic information processing. In addition to generating plausible or predictive outputs, knowledge needs to be interpreted, validated, legitimate, and used in context; all of which can be achieved through the use of AI. The four observable activities in the black box are acquisition, sharing, integration and application, which are all started when KMC begins.

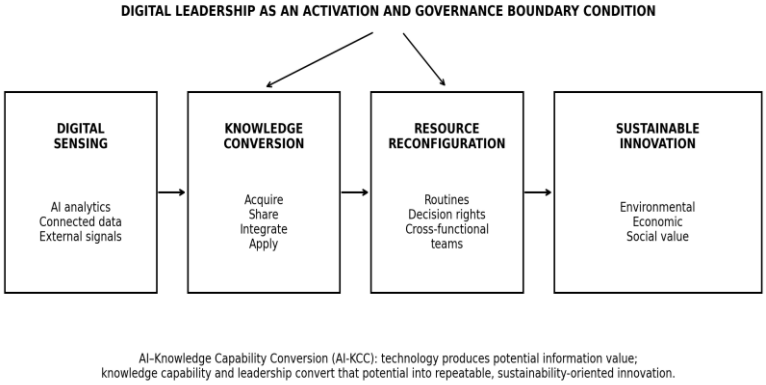

Figure 3. The AI–Knowledge Capability Conversion framework is a system and process to convert AI capabilities into knowledge.

Second, the framework is based on dynamic capabilities theory, but it treats KMC as a meso-level process of digital sensing to resource reconfiguration and vice versa. It is not necessary to develop a broad and general term for dynamic capability afterwards. Thirdly, it does not replace human knowledge by machine knowledge but adds machine knowledge to the KBV. Fourth, it is a logical explanation of the RBV logic of AI. While commercial tools are easily accessed, the more valuable and less easily copied resource is the package of proprietary data, domain expertise, governance, trust and learning processes that are found in the environment of that data.

In addition to the boundary condition the moderation result is observed. Digital leadership is not a substitute for technical and knowledge resources – it is the strengthening of their relationship. Therefore sustainable innovation is assumed to be a potential capability outcome of the adoption of technology conditionally.

Table 8. AI-KCC theoretical contribution

Lens	Extension	Observed implication
Dynamic capabilities	KMC converts AI-enabled sensing into seizing and transforming.	AIDT strongly predicts KMC, which predicts SI.
KBV	Machine outputs become knowledge through acquisition, sharing, integration and application.	Knowledge application has the largest KMC weight.
RBV	Advantage resides in the conversion bundle, not the increasingly tradable AI artefact.	The indirect effect exceeds the direct effect.
Digital leadership	Leadership activates and governs the conversion pathway.	Positive interaction and moderated mediation.
Sustainable innovation	Environmental, economic and social outcomes require integrated knowledge.	SI has balanced dimension weights and R^2 = 0.643.

These contributions are not only a mediation study, but have two special features. First, the mediator is based on the theoretical logic and broken down into the observed conversion routines. Secondly, the moderation result is the timing of mediators' emergence. They combine to give a conditional process explanation: AIDT results in a higher KMC level when DL is high, and a greater impact from KMC to SI. Success, partial success and failure can thus be explained within the same causal model through the framework.

The model is also a redefinition of the concept of sustainable competitive advantage in sectors that are involved in the intensive use of AI. Once the algorithm, the architecture of the infrastructure and the external expertise that enable the benefits are disseminated, that is not going to be the case for any given model architecture. Other more persistent differences emerge from: accrued decisions, vetted data sets; between technical and domain communities; and between routines to transfer learning, holding institutions accountable. They are socially complex and path-dependent complements. With individual technologies evolving, they can continue to add value, which is crucial for KMC.

VIII. Recommendations for managers and policies

Knowledge conversion as well as technical accuracy and savings should be assessed to determine the value of AI projects to managers. These can be quantified across a variety of metrics including time to validated decision, cross-functional review, reuse of learning and documented overrides and changes to controlled routines. Prior to deployment, each project should specify who will be the owners of the knowledge in the project, who the data stewards are and who has the decision rights and who has the escalation rights.

Table 9. Managerial implementation roadmap

Stage	Core practice	Illustrative indicator
Select	Link AI use cases to environmental, economic and social problems.	Expected resource, quality, access and decision value.
Connect	Create data stewardship and domain–technical teams.	Lineage coverage and cross-functional participation.
Validate	Use model review, expert challenge and decision logs.	Validation time and documented overrides.
Apply	Define decision rights, training and controlled process change.	Insight-to-action time and adoption.
Learn	Run outcome reviews and reuse knowledge across sites.	Lesson closure, reuse and model monitoring.

It is essential to design pathways for the development of AI projects that are multidisciplinary. Model cards, decision logs and expert annotations/exception reviews can be used to provide a link between coded outputs and tacit judgement and can be used to provide organisational memory. Digital leaders should be ambitious and also take the responsibility for the governance of the problem; setting priorities for problems, challenge and enabling time for people to spend learning, monitoring the impact of the deployment afterwards.

Sustainability goals are not add-ons for projects, they are to be considered as part of the project selection process. Use cases may be used as a comparison with criteria of resource reduction, quality, resilience, access and safety and impact on workforce. For policymakers and industry stakeholders, it is to be hoped that the same will be done with technology subsidies, shared standards, hybrid competencies, regulatory sandboxes and cross-firm learning networks and many other aspects.

The implementation should proceed gradually, allowing for the capability to grow and develop over time as opposed to technology hype that winds up in the organisation. Initially, companies need to possess some data ownership and restricted use scenarios. The next step should entail the creation of cross-functional interpretation and knowledge assets which are reusable. Only scale automated or generative decision support sites and partners thereafter. Without any conversion steps it can worsen any misapplications, local solutions and unquestioned assumptions.

Boards and regulators should also ask, "Who wins and who loses when it comes to the innovation of AI and who are the new risks?" Demand for computing can offset environmental improvements, efficiency gains can affect jobs and skills, digital services can increase access but exclude the poor in terms of access, and skills, populations can increase access to digital services but exclude access to the poor. Hence a well-designed SI scorecard should be employed hand in hand with the financial business cases. Responsible governance cannot happen without innovation capability: the reliability, legitimacy and transferability of the knowledge created is enhanced.

The framework also provides for a diagnostic for portfolio review. If the project has good models and good sharing, but poor application, it has a professional or data incompatibility issue; if it has good sharing and good modelling but poor application, it has an authority, incentive or validation issue; if it has good application and good modelling but poor sharing, it has a boundary-spanning issue. With this information, managers can locate an area of digital loss and instead make a selection for a capability intervention instead of an additional investment in technology. The portfolio diagnosis is to help decide which projects require scaling, redesigning or eliminating. It also enables comparisons to be made between R&D, manufacturing and regulatory as well as assuming that the same tools, routines, etc., are appropriate across these functions.

IX. The limitations and further studies are discussed.

The limitations of the perceptual and single-informant design, as well as the cross-sectional design, limit causal inferences and objective outcome assessments. Procedural and/or statistical remedies can help to reduce but not eliminate common method risk. Process, patent, quality, lifecycle and access indicators and surveys should be part of longitudinal and multi-source studies. Research might include testing of the various modes of mediation: acquisition, sharing, integration and application and digital capability to KMC and digital capability to innovation capability and SI. Other moderators are learning culture, data governance maturity, environmental dynamism and regulatory intensity. The cross-country study and comparison of generative AI, digital twins, and Industry 5.0 can analyse the role of the new digital agents in the knowledge validation, human oversight and sustainability trade-offs.

X. Conclusion

AI is also making a difference in the field of sustainable innovation by turning the digital outputs into changes, sharing them, and making them applicable in the field of pharmaceutical companies. Development is underway in the direction of a central mechanism – KMC – and is supported by digital leadership. The AI-KCC framework thus covers the advantage not in terms of technology but in terms of the routines and governance that are established and worked out in the company.

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