A PROCESS MODEL OF MANAGERIAL PHRONESIS IN THE AGE OF GENERATIVE AI

Forthcoming in *Academy of Management Review*

Dirk Lindebaum
University of Bath, UK
School of Management
d.lindebaum@pm.me

Natarajan Balasubramanian
Ohio State University, USA

Mehreen Ashraf
Cardiff Business School, UK

Patrick Haack
HEC Lausanne, Switzerland

Abstract

Managerial phronesis involves first-hand experience that helps managers make moral and context-specific judgments at work in pursuit of the common good. Yet, as managers increasingly rely on Generative AI (Gen-AI) at work, many of these first-hand experiences are replaced by synthetic outputs. While past research has investigated how Human-AI interactions alter managerial agency, we do not know *why, how,* and *under which conditions* Gen-AI affects the development of managerial phronesis. Answering these questions is important because phronesis underpins much of knowledge use in organizations. Consequently, we develop a baseline model that advances our understanding of how phronesis emerges in the absence of Gen-AI, introducing conceptual innovations that explain how *new* experiences are generated. We then extend this model by explaining why and how Gen-AI shapes the development of phronesis. Specifically, we theorize how Gen-AI can shift the development of phronesis towards what we term epistemic *de-skilling*, when conditions of perceived time pressure prompt cognitive offloading of tasks, and towards epistemic *up-skilling*, when conditions of accountability activate managerial reflexivity. We discuss the theoretical and practical implications of our model and articulate an agenda for future research.

Keywords: Cognitive Offloading, Generative AI, Learning, Phronesis, Process Theorizing, Reflexivity, Routines, Work Design

Acknowledgments: We gratefully recognize the invaluable feedback provided by Yash Raj Shrestha and Igor Pyrko on an earlier version of this article. Likewise, we thank our colleagues at the University of Bath School of Management, ESCP Berlin, Trinity College Dublin, and the participants at the EGOS 2024 colloquium for their probing questions and comments concerning our article and model. Finally, our article benefitted enormously from the exemplary theoretical steer from Associate Editor Sergio Lazzarini, as well as generous and developmental comments from the reviewer team.

Note: We herewith certify that this article represents original and independent scholarship. That is, generative AI was not used in the idea-generating phase of this article, nor was it used to assist in the writing or editing of this article. Note that Dirk Lindebaum is an advocate and owner of “AI-free scholarship®”, which is a registered trademark.

Managerial phronesis, the ability to make moral and context-specific judgments in complex situations in pursuit of the common good (Tsoukas, Hadjimichael, Nair, Pyrko et al., 2024), underpins much of knowledge use in organizations. Through experiential learning, which transforms first-hand experience into knowledge (Kolb, 1984), phronesis develops over time in terms of: (i) moral insight (the ethical dimension of ends); (ii) contextual sensitivity (understanding the particulars of a situation); and (iii) practical know-how (tacit and embodied skills) (Shotter & Tsoukas, 2014). Consequently, the development of phronesis relies on the collection of first-hand experience in a social context, and how managers get socialized into *what ought to be done* when facing indeterminate, value-laden problems (Flyvbjerg, 2001). However, managers now increasingly rely on the use of generative AI (Gen-AI) to complete tasks at work (Dell'Acqua, McFowland, Mollick, Lifshitz et al., 2026). Because Gen-AI concerns the "production of previously unseen *synthetic* [here, textual] content . . . through generative modelling" (García-Peñalvo & Vázquez-Ingelmo, 2023, p. 7, italics added), it can only offer synthetic[1] approximations to real-world situations rather than the direct first-hand experience on which managerial phronesis depends.

The contrast between knowledge generated through first-hand experience - and synthetic knowledge generated through Gen-AI outputs - raises concerns for scholars interested in managerial phronesis and knowledge generation more generally (Contu, 2023; Gerlach & Lange, 2026), as to the ways in which the use of Gen-AI may shape phronesis, especially when Gen-AI outputs substitute first-hand experience. For one thing, the synthetic and codified nature of Gen-AI outputs may reduce a manager's agency to develop useful and usable knowledge (Aguinis & Cronin, 2022) in a given situation by inserting 'distance' between managers and those experiences essential for developing their phronesis. In turn, this distance may weaken managers' ability to

[1] 'Synthetic' in the sense that Gen-AI outputs mimic, rather than genuinely represents, real-world experiences (Jordon, Szpruch, Houssiau, Bottarelli et al., 2022), such that advice from Gen-AI that adding an ingredient will make a recipe taste better is unfounded on experience since it cannot taste.

recognize the relational and contextual consequences of their actions for relevant stakeholders, thereby undermining morally informed judgment in pursuit of the common good. For another, the 'distance' between synthetic data and real-world experience can motivate managers to enrich their phronesis by activating their reflexivity, defined as "questioning our relationship with our social world and the ways in which we account for our experience" (Hibbert & Cunliffe, 2015: 180). Hence, managers can develop their agency to acquire more useful and usable knowledge based on their reflexive endeavors. Crucially, it is the limitation of Gen-AI to explain the reasoning behind outputs (Sarkar, 2024) that helps activate reflexivity to develop managerial phronesis.

Turning to how Human-AI interactions (Raisch & Fomina, 2025) alter managerial agency enables us to theorize the influence of Gen-AI on the development of phronesis. In this respect, we currently lack a clear understanding of why and how Gen-AI engenders processual shifts in the development of managerial phronesis, as well as the boundary conditions under which these shifts are likely to occur. Since phronesis underpins much managerial knowledge use it work (Shotter & Tsoukas, 2014), it is theoretically and practically key to ask *why, how,* and *under which conditions* Gen-AI affects the development of managerial phronesis.

Two related aims follow from this question. We first develop a baseline process model that explains why and how humans develop phronesis in the *absence* of Gen-AI. As managerial phronesis develops through learning, we build on existing learning theories (e.g., Kolb, 1984), which focus on experience *after* the fact. After all, managers can reflexively interrogate the variables behind decisions that have yielded undesirable results (Argyris, 2002). Yet, to focus on after-the-fact learning alone is insufficient in the age of Gen-AI; we need to understand how new managerial experience develops by way of *prospective* learning (Lindebaum, 2024), which may involve anticipating ethical dilemmas not captured in existing models and training data. Hence, we extend existing works (e.g., Kolb, 1984) by illuminating the processes behind the emergence of new experiences; that is, being motivated to think outside the box, a point we derive from the work of Kant (1781/2007) and Dewey (1922). Importantly, we focus here on socially embedded first-hand experience (rather than individual task performance), for managers develop phronesis through social encounters and socialisation practises at work that shape what they notice, how they interpret situations, and what they come to regard as appropriate action (Tsoukas et al., 2024). Thus, our baseline model aims to theorize how new first-hand experiences are generated and how these experiences subsequently can help activate managerial reflexivity. This permits us to theorize the iterative interplay between novel situated action and post-experience reflexivity in the development of phronesis, including its subcomponents of moral insight, contextual sensitivity, and practical know-how.

Having established the baseline process, the introduction of Gen-AI as an epistemic technology (Alvarado, 2023) that produces synthetic content informs our second aim, namely, to examine the processual shifts through which Gen-AI affects the process of developing managerial phronesis. In this regard, Gen-AI is unlike technologies that advance human learning (for more detail, see also Alvarado, 2023). While a telescope helps us see objects that cannot be seen with the eye and thus improves our experience of the world, Gen-AI relies necessarily on codified information and, therefore, cognitive offloading to Gen-AI can become a codified substitute for real experience. Extending the baseline model, we theorize processual shifts that explain how managerial use of Gen-AI risks diminishing phronesis through a process we term *epistemic de-skilling,* whereby managers cognitively offload tasks to Gen-AI under conditions of perceived time pressure. On the other hand, managers can enhance phronesis through the process of *epistemic up-skilling*, whereby prompts from Gen-AI strengthen managerial reflexivity under conditions of perceived and formal accountability.

Our article offers three theoretical contributions to management research. First, our model introduces conceptual innovations that advance our understanding of how managerial phronesis develops. Specifically, we build on Kant (1781/2007) and Dewey (1922) concerning the generation of new managerial experience that do not feature in existing learning models (Kolb, 1984). In doing so, we highlight that humans have distinctive capabilities to generate new experience. Second, building on this foundation, we theorize the processual shifts through which Gen-AI shapes the process of developing managerial phronesis, as well as the boundary conditions under which these shifts are more likely to occur. Although these shifts may arise under a variety of organizational conditions, perceived time pressure can lead managers to offload cognitive effort to Gen-AI both during task performance and subsequent reflection, thereby weakening their motivation to learn from experience and interrogate their choices. Conversely, perceived and formal accountability can prompt managers to engage with Gen-AI's inherent explanatory silence, encouraging deeper reflexivity about the reasoning that underlies their decisions for increased epistemic up-skilling. Examining these processual shifts, along with the boundary conditions, provides a perspective that is currently absent in existing works on learning and knowledge work in the age of Gen-AI (e.g.,Dell'Acqua et al., 2026). Third, adopting a process perspective (Cloutier & Langley, 2020) deepens our understanding of the dynamic interaction between human experience and Gen-AI in the context of developing phronesis. This helps us theorize both inhibiting and enabling effects of Gen-AI, which may intensify with each iteration of the feedback loop. At the same time, our process model features conceptual versatility that enables exploring a range of phenomena in conjunction with Gen-AI's impact on knowledge creation, such that phronesis in the model could be substituted with critical thinking (Larson, Moser, Caza, Muehlfeld et al., 2024), creativity (Cronin & Loewenstein, 2018), and entrepreneurial opportunities (Nair, Gaim & Dimov, 2022).

Our process models also offer practical value for managers by showing: (i) how phronesis develops in the absence of Gen-AI through first-hand experience that is socially embedded; (ii) the risk of epistemic de-skilling when managers fail to develop phronesis as a source of useful and usable moral knowledge, and (iii) how Gen-AI can enhance managerial phronesis when it is used to develop managerial reflexivity. More broadly, our theorizing suggests that organizations can manage these outcomes through work design arrangements (Parker & Grote, 2022) can help organizations mitigate the potential costs of epistemic de-skilling, while amplifying the benefits of epistemic up-skilling at the workplace (however challenging the latter will be, as highlighted later).

The next section introduces our baseline model of phronesis, with brief but necessary exposure to learning theories. We then incorporate Gen-AI into the baseline model and show why and how it reshapes managerial phronesis through epistemic de- and upskilling. Next, we introduce boundary conditions that account for why learning in Human-AI interactions may cause a shift to epistemic de-skilling and up-skilling in relation to phronesis. We conclude by discussing implications of our findings and presenting an agenda for future research.

A BASELINE MODEL OF DEVELOPING MANAGERIAL PHRONESIS

As indicated before, phronesis integrates three interwoven strands: (i) moral insight, (ii) contextual sensitivity, and (iii) practical know-how (Shotter & Tsoukas, 2014). In our baseline model, *a priori* knowledge and general epistemic motivation do not develop these components directly; rather, their mutual causality helps managers seek out socially embedded first-hand experiences beyond what they already know. These experiences then cultivate the three components of phronesis in distinct ways. Moral insight develops when managers confront morally puzzling situations through social interaction and learn to recognize the normative consequences of their own and others' actions (Moser, den Hond & Lindebaum, 2022). Contextual sensitivity develops as managers persist with their efforts to identify relevant local, relational, and organizational particulars. Practical know-how develops through repeated application, practice, and reflexive interrogation of skill and knowledge over time.

In addition to these considerations, phronesis shares structural affinities with *techne,* or skilled practice (Stichter, 2018; Tsai, 2020), it differs, however, in its *telos*: rather than pursuing technical mastery, it concerns *acting well* and the *right action* in situations where norms and outcomes are contested (Tsoukas et al., 2024). Phronesis is, therefore, not simply a skill, but skilled action guided by the cultivated capacity to discern what matters in a concrete context (Nussbaum, 2001). This is a crucial point - phronesis has both a retrospective and prospective angle – it develops in “response to, or in anticipation of, challenging particularities” (Moberg, 2007: 536).

With this in mind, Figure 1 depicts our baseline model, which explains how managers develop phronesis in the *absence* of Gen-AI. Note that in this and subsequent models, the boxes refer to discrete individual capacities or events, while the rhombi depict processes. We build on experiential learning theory, which explains how individuals process experience after it has occurred (e.g., Kolb, 1984). Experiential learning usefully shows that exposure to events alone is insufficient: learners must deliberately engage with, and reinterpret their experiences through reflective effort and active experimentation (Chan, 2022). Because this tradition remains mostly oriented toward retrospective reflection, it focuses less on how managers generate new first-hand experience in anticipation of novel or morally ambiguous problems. Thus, we extend the conception of learning and the development of phronesis to include prospective adaptation (Lindebaum, 2024), insofar as it can be applied to creating future conditions of possibility and help managers find solutions to current or anticipated workplace problems by engaging productively with ambiguity (Moberg, 2007).

Insert Fig 1 about here

We mobilize Kant’s (1781/2007) *a priori* knowledge (knowledge independent of prior experience) and Dewey’s (1922) idea of the habit of learning. We use these not to develop a theory of human learning, but to explain how managers become capable of seeking experiences beyond what they already know. Kant’s (1781/2007) emphasis on the ‘transcendental’ is key here, for it “denote[s] the mental realm that precedes the empirical and makes experiences possible” (p. xxxiv). Two interdependent capacities related by mutual causality constitute the core of our baseline model (see Figure 1): Kant’s *a priori* knowledge and general epistemic motivation, inspired by Dewey (1922) and defined in terms of acquiring the habit of learning.

First, Kant's (1781/2007: xxxv) *a priori* knowledge matters because "if all we have is an experience, all we can learn is the inevitability of repeating it" (Levine, 2002: 1251). Thus, *a priori* knowledge can be considered as a mechanism of deduction, opening up space for novel insights not rooted in prior experience, such when we state that "all roses are not red" (O'Sullivan, 2017: 22) [2]. This statement invites deduction concerning roses that are not red (now or in future), but what might their colors be? We argue that the deduction that underpins *a priori* knowledge works through choices that are "lateral and unpredictable, associative and idiosyncratic . . . [even] unexpected, strange" (Deresiewicz, 2023), or plainly, choices that have not been entertained before. These choices would not be activated if we consider statements with an in-built confirmation, such as "all bachelors are unmarried" (O'Sullivan, 2017: 22). There is no scope to learn anything new about unmarried bachelors as per Kant (1781/2007). We pair *a priori* knowledge with what we term general epistemic motivation, derived from the work of Dewey (1922). He identifies a reflexive capacity to avoid 'crusty' habits that are no longer fit for purpose in dynamic person–environment interactions. Individuals can cultivate "the habit of learning" where "it is possible for man to learn the habit of learning" (p. 105).

Reiterating that most existing learning theories focus on retrospective learning (*after the fact*), the mutual causality between *a priori* knowledge and general epistemic motivation can be explained as follows. First, general epistemic motivation may trigger a search for differently

[2] Two clarifications are needed here. First, we do not invoke a strong version of 'pure' *a priori* knowledge, as "nothing empirical is mixed in with it" (Kant, 1781/2007: 38) Yet, we can come to know conditions of possibility of an object though reasoning too (not just by experience). Most of our knowledge may begin with experience, but "it does not follow that it arises from experience" (p. 37). When we suspend knowledge to make room for new insights, we can also do that by drawing on a general rule, which is itself derived from experience, but applied in novel or different context for which no direct first-hand experience exists. Understanding gravity means we know a house will tumble if the foundations are removed, yet we "could not know this entirely a priori" (Kant, 1781/2007: 38). We argue that the 'red rose' example can be applied in the same spirit here – as it springs from the universal rule that not all objects are roses, not all roses are red, and not all reds refer to the color of roses. Second, we appreciate that Gadamer (2004) uses the concept 'pre-judgment,' which involves a "a fusion of horizons" (Regan, 2012: 291) when individuals fuse the 'familiar' with the 'alien' in interpreting text. However, our understanding of how the term 'alien' is mobilized in Gadamer's (2004) work suggests a more passive connotation for the reader. Specifically, "the alien aspects of text are what is the unknown, challenging the interpreter's familiar worldly horizons that assimilates old knowledge into new understanding" (Regan, 2012: 293). Kant's notion of *a priori* knowledge, by contrast, has more active connotations in the sense of creating (rather than reacting to) new concepts, categories, and ideas. We thank an anonymous reviewer for prompting these reflections.

colored roses, given that ‘not all roses are red’. Under this formulation, general epistemic motivation can enable *a priori* knowledge, because a motivational source needs to be present for activating *a priori* knowledge and for ‘thinking outside the box’, both of which are cognitively effortful activities (see e.g., Clay, Mlynski, Korb, Goschke et al., 2022). If not all roses are red, then what other colors (or shapes or scents) might roses have? In a managerial context, an HR manager who knows that not all employees are motivated by money might wonder how else to motivate them. Likewise, a manager exercising general epistemic motivation can create new organizational routines before existing ones become dysfunctional, which is another example of mobilizing Kant’s *a priori* knowledge in management. By contrast, initial attempts by a manager to develop *a priori* knowledge, if successful, can prompt future eagerness to re-experience the gratification of having transcended existing knowledge to find a novel solution to a novel problem. Thus, the experience of *a priori* knowledge fans general epistemic motivation over time. In sum, a *priori* knowledge provides the conceptual resources for asking what else might be possible, while general epistemic motivation turns this possibility into active engagement with new first-hand experiences. This mutual causality ultimately explains how managers seek out situations that extend their existing understanding. However, this mutual causality is also more; it is a central ‘human’ factor in the process of learning, especially in terms of knowing-*why* and knowing-*how* (Quinn, Anderson & Finkelstein, 1996). In fact, Gen-AI is unable to entertain and answer these questions, for it does not care for the conditionality of human existence - we are conditioning and conditioned creatures bound to specific socio-historical contexts (Arendt, 1958/1985).

Applied to our model, this mutual causality steers individual attention toward richer and more varied first-hand experiences (see first rhombus on the left). Recall that existing learning theories start here, at the juncture of first-hand experiences after the fact in dynamic person–environment interactions (Kolb & Kolb, 2005). In these interactions, first-hand experiences are accumulated and are organized into cognitive ‘constructs’ (Kelly, 1955), such that “the number of constructs a person uses may indicate [their] cognitive complexity, or the fineness with which

[they] can discriminate between people" (Forgas, 1985: 40). As managers exercise agency and consider why their usual approaches fail, they weave new observations into abstract hypotheses, preparing them for further experimentation (Kolb & Kolb, 2009). This cycle transforms raw encounters into durable knowledge. In contrast to Kolb's purely reflective loop, our model emphasizes the anticipatory role of *a priori* knowledge and the energizing role of general epistemic motivation in generating novel (but as yet unimplemented) solutions for anticipated problems. Once acted on, in response to an anticipated problem (see second rhombus on the right in Figure 1), the resulting first-hand experiences are transformed into phronesis through the process of experiential learning (Kolb, 1984). We discuss this below.

In a managerial context, phronesis unfolds in the moment of choice, guided by an ethical compass and grounded in situational awareness developed from a set of first-hand experiences (Antonacopoulou, 2010). Shotter (2011) describes this as 'withness-thinking,' a reflexive mode in which actors simultaneously inhabit the flow of events and critically question their own values, ends, and means. As specified above, this reflexive mode applies to all three components of phronesis, albeit in slightly different ways; we focus on first-hand experiences that are socially embedded rather than merely task-focused. Because the development of moral insight, contextual sensitivity, and practical know-how has been specified above, we do not reproduce these component-level mechanisms in Figures 1, 2a and 2b, and focus on phronesis as a whole. At the same time, Table 1 summarizes how each component arises in the baseline model and how it is reshaped by Gen-AI through epistemic de and up-skilling.

Insert Table 1 about here

However, the transformation of 'in-the-moment' experience into sustained phronesis requires conscious reflexive effort of managers *after* such experiences. This is where teleological epistemic motivation can fan individuals to reflexively interrogate the governing variables that underpin decisions (Argyris, 2002). Unlike general epistemic motivation, which fuels a desire for broad exploration and learning *before* the fact, teleological epistemic motivation can activate reflexivity *after* the fact, thus necessitating a distinctive positioning of both versions of epistemic motivation in the model. It implies a retrospective motivation to the question *why* behind the values and ends we pursue—hence the qualifier "teleological"—precisely at those moments when after-the-fact routine fixes prove inadequate (Argyris, 1982). According to Lindebaum and Fleming (2024: 7), we (humans) are unique in possessing "the ability to question and transcend the axiomatic foundations of processing" our own experience—a capacity that underpins our ability to enact phronesis, the seamless integration of moral insight, contextual sensitivity, and practical know-how in the heat of action. Furthermore, teleological epistemic motivation does more than prompting managers to correct mistakes after the fact; it also activates a reflexive stance in which one deliberately "questions what we, and others, might be taking for granted, what is being said and not said, and examines the impact this has or might have" (Cunliffe, 2016: 741).

Empirical research confirms that this close coupling of reflexivity and phronesis is a defining feature of genuine human learning. Ames, Serafim and Zappellini (2020) suggest that reflexive prompts woven into experiential exercises can significantly enhance learners' in-action moral judgment, while Dierksmeier, Habisch and Bachmann (2018) promote pedagogies that center on reflexive practice precisely because they nurture phronesis—not just technical mastery. In so doing, reflexivity transforms managerial learning from concrete experience into an ethical laboratory through experimentation (Antonacopoulou, Bento, Edward, Hawkins et al., 2023), ensuring that learners generate novel and value-infused responses, instead of simply processing experience.

Having laid out how phronesis develops, we discuss the potential impact of Gen-AI on this process. As employees increasingly rely on Gen-AI to perform asks, the nature and extent of their first-hand experiences are likely to change substantively. We begin with a brief review of prior work on Human–AI interactions, with a focus on learning for managerial phronesis. We then examine how the introduction of Gen-AI can generate processual shifts that, depending on the boundary conditions at hand, may lead to either epistemic de-skilling or up-skilling, as discussed in the following sections[3].

DEVELOPING PHRONESIS IN HUMAN-AI INTERACTIONS

To unpack how Human–AI interactions influence the development of phronesis, we begin by examining (i) how agency is distributed in that interaction, (ii) how learning unfolds within that agency, and (iii) how these processes inform the development of phronesis.

First, a growing body of scholarship on Human–AI interaction now suggests that agency is not a static property located in either the human or machine, it is dynamically distributed across both (Faraj & Pachidi, 2021; Glaser, Sloan & Gehman, 2024). Rather than treating Gen-AI as a tool used by an autonomous human actor, recent frameworks have adopted a relational view of agency as conjoined (Murray, Rhymer & Sirmon, 2021), or co-constituted in relation to learning (until co-constitution is supplanted by dominant AI inputs in Human-AI interactions, see Moser et al., 2022). In Human-AI interactions, Gen-AI may offer greater information-processing capacity, while humans bring their lived experiences, knowledge, and ability to question Gen-AI's propositions (Eicke, Foege & Nüesch, 2025). For example, Amershi, Weld, Vorvoreanu, Fourney et al. (2019) propose a typology in which AI agents play roles that vary in directiveness and autonomy, ranging from rule-enforcing coaches to co-creative collaborators. These roles shape the extent and nature of human involvement. Directive hints require critical evaluation, while collaborative scenarios demand situated, context-sensitive judgments. Collectively, these studies underscore a key shift in the discourse, whereby Human-AI interactions involve the dynamic co-configuration of roles, intentions, and influence, not just automation and control. Of

[3] Two points are worth noting here. First, extending the terms 'de-skilling' and 'up-skilling' into the epistemic sphere is warranted beyond the enhancement or loss of task competencies (Penn & Scattergood, 1985), both in relation to manual tasks (e.g., artisanal carpentry skills) and mental tasks (e.g., the introduction of the calculator). In saying so, we subscribe to the view of skills as cognitive abilities (Rindermann, 2018). Second, the question of whether epistemic de/up-skilling existed before the arrival of Gen-AI is permissible. Examples of epistemic de-skilling before the arrival of Gen-AI can be seen in the introduction of writing (and later printing), both of which were said to impair memory (Socrates felt this way, for instance). Similarly, the introduction of the calculator was believed to undermine mental arithmetic skills. An example of up-skilling can found in prior works on 'reading for understanding'—the act of advancing oneself through intellectual effort when the author of a book seems intellectually superior (Adler & van Doren, 1940/1972).

note, recent empirical work underlines that this 'co-configuration' implies that "human–AI interactions alter processes underlying human perceptual, emotional and social judgements, subsequently amplifying [AI] biases in humans" (Glickman & Sharot, 2025: 345). Further, recent commentaries on studies posted on a pre-print server suggest that "we might be overestimating our ability to spot check the content that LLMs produce—and underestimating how vulnerable we are to being manipulated by them", such that "instead of being a neutral collaborator, [the researchers] identified the AI as a "power persuader" that "persuasion bombed" users to accept its conclusions" (Stackpole, 2026). Thus, in addition to clarifying *how* agency is distributed across human and AI actors, we now understand better how these interactions shape learning underlying phronesis.

Second, in examining how learning unfolds within Human-AI interactions, the notion of co-constituted agency in human learning and technology becomes particularly relevant (Faraj & Pachidi, 2021; Guile & Popov, 2025). For instance, Raisch and Fomina (2025) define an interactive search as humans and AI agents define a problem and search for solutions jointly, with mutual learning occurring continuously between these agents. Eicke et al. (2025) extend this pattern into an iterative and interactive evaluation process. Similarly, Kemp (2024) conceptualizes Human-AI learning as a dynamic, phased process in which AI actively shapes user behavior. Together, these studies conceptualize AI as an active learning provocateur, but do not theorize how Human-AI interactions shape the iterative development of managerial phronesis.

Third, the above perspectives imply that learning is not neutral, unidirectional, or automatic, but co-constituted, moving back and forth from human to AI and vice-versa (but not in balanced fashion over time, see Glickman & Sharot, 2025; Moser et al., 2022). Unsurprisingly, concerns have emerged over the extent to which Human-AI interactions may impinge on phronesis. Eisikovits and Feldman (2022) caution that "AI is gradually replacing practical decision making in our work lives" (p. 189), thus expressing concern about an associated decline in the human capacity for judgment. In a similar vein, Balasubramanian, Ye and Xu (2020) suggest a risk of weakened organizational learning if machine learning replaces humans in routines essential for human on-the-job learning (see also Gerlach & Lange, 2026).

However, others argue that AI can serve as a source of epistemic dissonance-friction, which interrupts habitual thinking and provokes critical reflection (Miller, 2019; but see Ramsoomair, 2025, for a counterargument). When Gen-AI outputs diverge from user expectations, they can surface hidden assumptions and prompt moral and cognitive deliberation. In this sense, Gen-AI does not function as a substitute for wisdom, but as a stimulus for its development. However, this possibility depends on how AI is designed, institutionalized and embedded in work practices (Coeckelbergh, 2020). Systems that support reflexive practice, rather than impose rigid decisions, are more likely to enable phronesis because wise judgement requires attention to context, care for others and responsibility for outcomes (see e.g., Contu, 2023), rather than rule-following or algorithmic rationality alone. Thus, Gen-AI cannot replicate phronesis, but when accompanied by social structures that value accountability, transparency, and pluralism (Islam & Greenwood, in Brown, Davison, Decker, Ellis et al., 2024), it may help managers cultivate the moral and epistemic capacities upon which phronesis depends.

In what follows, we extend and deepen these initial explorations of Human-AI interactions in the context of phronesis. To do so, we extend our baseline model and adopt a dynamic conceptualization of Human-AI interactions to analyze the processual impact of Gen-AI on developing phronesis. We begin by examining the processual shifts through which Gen-AI may lead to epistemic de-skilling across repeated learning cycles. While we elaborate on the boundary conditions later, bearing in mind that perceived time pressure amplifies these dynamics.

The process of epistemic *de*-skilling

We identify two critical junctures in the baseline model that introduce processual shifts and theorize these shifts as leading toward epistemic de-skilling (see the red and dotted boxes 1a and

1b in Figure 2a). These shifts risk undermining the development of phronesis by diminishing managers' capacity for moral insight, contextual sensitivity and practical know-how[4].

Insert Fig 2a about here

The first juncture is the individual decision to cognitively offload problem-solving to Gen-AI *before* and without activating the mutual causality between *a priori* knowledge and general epistemic motivation. When this occurs, the decision to offload weakens *a priori* knowledge, general epistemic motivation, the mutual causality between them, and ultimately managerial agency. Seen in this light, *a priori* knowledge and general epistemic motivation are 'offloaded' to Gen-AI (processual shift 1a), and thus not activated or developed over time (León-Domínguez, 2024). As for general epistemic motivation, Friedland (2019) argues that cognitive 'offloading' can lead to increased individual passivity (because we accept help to complete a task). When this happens, that passivity lessens both contextual sensitivity and practical know-how. Friedland (2019) further argues that diminished participation can lead to emotional disengagement from the workplace (for empirical evidence concerning the latter, see Liu, Wu, Ruan, Chen et al., 2025), thereby weakening possible moral insights.

Offloading occurs when Gen-AI enables individuals to substantially reduce cognitive and emotional engagement that seems costly in the short-term, but is essential for the maintenance of longer-term learning. In such 'offloading' scenarios, the short-term costs of activating *a priori* knowledge and general epistemic motivation obscure the key benefits which will manifest in the future. While learners may benefit from Gen-AI use to complete tasks in standardized settings (exams or work-related - see Bergenholtz, Vuculescu, Günzel-Jensen & Frederiksen, 2026), this does not equate per se with knowledge gain and transfer (Horvath, 2025). Recent empirical studies underline this development, arguing that Gen-AI "may promote

[4] To orientate the reader, we theorize a cumulative logic; any initial decision to offload problem-solving to Gen-AI (shift 1a) can make subsequent departures (shift 1b) from the baseline learning process *more* likely (and opportunities to solving problems oneself *less* likely).

learners' dependence on technology and potentially trigger "metacognitive laziness"". Other studies (Bergenholtz et al., 2026) report that, while low performing students improved on a time-pressured business school exam, they experienced "cognitive load relief by copying chatbot output, thus bypassing the analytical work the task requires" (p. 1). Further, empirical studies show that, although students relying on Gen-AI (LLM here) experienced lower cognitive load in an information gathering exercise (involving recommendations and justifications), these students also showed lower-quality reasoning and argumentation in their final recommendations, in contrast to students who used traditional search engines (Stadler, Bannert & Sailer, 2024).

By diminishing our motivation to explore what can be known beyond what we know *now* or what might be known *in the future*, the use of Gen-AI turns *a priori* knowledge into an under-nourished realm (León-Domínguez, 2024). This impoverishment is relevant because, as indicated before, *a priori* knowledge connotes active engagement (and thus agency). With *a priori* knowledge impoverished, the wherewithal of managers to ask such questions is diminished, resulting in more muted possibilities to nurture moral insights, contextual sensitivity and practical know-how to activate alternative contexts and situations (see also Table 1).

This 'short-circuiting' of active engagement induced by overreliance on Gen-AI bypasses the development of phronesis, preventing managers from engaging in critical evaluation. Managers stop interrogating their cognitive biases and lose the ability and agency to reflect upon or challenge prevailing social norms (Larson et al., 2024). For example, consider managers who rely on Gen-AI to propose a business strategy based on recommendations from a retail sales data set. Without fully understanding the reasoning or potential biases embedded in the AI-generated recommendations (or finding it prohibitively time consuming to acquire such understanding), managers may act on the AI-generated recommendations without analyzing it critically. In doing so, they reduce their engagement with moral insights, contextual sensitivity and practical know-how concerning thinking about possible futures (such as new sales opportunities *not* derived from direct prior experience).

Consistent with this, Alon-Barkat and Busuioc (2022) have found in their study that public-sector managers follow algorithmic advice, even when explicit warning signals from other sources suggest caution, leading to commission errors and overreliance on AI outputs. Likewise, experimental studies of automation bias have revealed that managers will follow incorrect AI suggestions without checking their validity across diverse decision tasks (Vered, Livni, Howe, Miller et al., 2023). This risk of taking short-cuts is amplified when Gen-AI models are customized using past organizational data. Such models yield responses that reflect past expectations and experiences in the narrow context of that organization, leading to fewer questions and learning opportunities (Balasubramanian et al., 2020). In this case, Gen-AI mediated experience progressively erodes moral insights, contextual sensitivity and practical know-how through abstractions from local conditions to the lived consequences of managers' decisions (Moser et al., 2022). As indicated in Figure 2a through the reference to Time 1 and Time 2+n, individuals cycle over time through the iterative learning process. As a result, deterioration in the knowing-why due to cognitive offloading leads to diminished knowing-how and knowing-what, given that *why* questions constraints answers to the how and what questions (e.g., we can only answer how to regulate emotion once we understand why a specific context dictates the regulation of emotion in one way rather than another - Charland, 2011).

The second juncture (processual shift 1b in model 2a) implies that, instead of 'throwing' ourselves into the real-world with all its social complexity and messiness (Holt & Zundel, 2023), Gen-AI reduces first-hand experiences and informs experiential learning through the lens of technological mediation. That is, "ways in which technologies co-shape, enable, challenge or change the engagement of people with the world" (de Boer, Hoek & Kudina, 2018: 302). The kind of digital mediation through Gen-AI we have in mind here differs from other instances of technological mediation, such as using remote thermal-sensing technology to measure the temperature of a hot object, rather than touching it directly. After all, this form of mediation is beneficial, since touching the object could lead to injuries. Yet, in this example, technology only provides inputs (e.g., the temperature of the object) that further experiential learning by humans. Gen-AI, by contrast, offers largely contextless (i.e., synthetic) substitutes for direct first-hand experience. As Vallor (2024) points out, "[AI systems don't] have the slightest sense of their place and role in this world, much less the ability to experience it." This is why first-hand experiences, collected through 'management by walking around' (Peters & Austin, 1985) and interacting with staff or customers can provide managers with vital clues about how well (or not) organizational processes work.

In the context of work, it is instructive that the main reason managers use Gen-AI is to generate content or ideas, while the second most cited reason is to fulfil therapeutic or companionship needs (Zao-Sanders, 2024). Thus, rather than collecting first-hand experiences in the social world, and being able to mobilize these experiences for problem-solving in a concrete context, the continuous offloading of tasks at work implies that technologically mediated experiences become increasingly divorced from first-hand experiences at work. The epistemic consequences of outsourcing phronesis to Gen-AI are unlikely to be uniform across its constituent dimensions, while reduced agency is likely to arise overall. First, moral insight is most dependent on socially embedded first-hand experiences which weaken when managers become displaced from the normative deliberation through which competing stakeholder claims and ethical trade-offs are considered. For example, reliance on AI-generated recommendations in hiring, evaluation, or resource allocation may reduce managers' engagement with questions of fairness and downstream harm (Binns, Kleek, Veale, Lyngs et al., 2018). Second, when managers rely on generalized AI-generated framings of situations, contextual sensitivity diminishes through reduced attentiveness to local nuance and situational exception. For instance, when standardized recommendations obscure personal, political, or relational dynamics that render superficially similar cases meaningfully different (Shotter & Tsoukas, 2014). Finally, practical know-how erodes when managers are displaced from the situated enactment and diagnostic problem-solving through which tacit, embodied judgment-in-action is acquired, rather than directly navigating interpersonal conflict or operational ambiguity (Polanyi, 1966).

From the perspective of our model, Gen-AI-enabled cognitive offloading and technological mediation can limit an individual's ability to reconstruct experiences in real time and over time, potentially "make[ing] students [or managers] omit the whole learning process, including students [or managers] developing their judgment, their ability to deal with 'aporetic' [or puzzling] situations, and the continuous reconstruction of experience" (Lindebaum & Ramirez, 2024: 343). This leads to an impoverishing process of epistemic de-skilling. Such processual shifts naturally result in fewer opportunities to engage in teleological epistemic motivation after experiences (i.e., efforts to activate individual reflexivity), thus reducing the development of phronesis. Over the longer term, this pattern will cause an increasingly enfeebling loop for the development of phronesis, referred to in Figure 2a as the 'Gen-AI inhibitor effect'. Conceptually, the red double arrow represents a growing distance from the baseline model, via multiple iterations, toward less managerial phronesis over time. With each iteration, the arrow grows longer, indicating that the Gen-AI inhibiter effect is increasing. Next, we turn to the contrasting path of epistemic up-skilling. Bear in mind that perceived and formal accountability as boundary condition amplifies these dynamics.

The process of epistemic *up*-skilling

Gen-AI also affects the baseline process model of developing managerial phronesis through epistemic up-skilling, where managers use interactions with Gen-AI to deepen reflexivity and strengthen the experiential development of moral insight, contextual sensitivity, and practical know-how (see green lines in Figure 2b)

Insert Fig 2b about here

In this regard, the inability of Gen-AI to engage in a transcendental inquiry à la Kant implies that Gen-AI cannot engage in its own epistemic limitations and possibilities (Lindebaum

& Fleming, 2024). However, this Gen-AI failure can be converted into an opportunity for transforming first-hand experiences into augmented managerial agency and phronesis, where managers (i) recognize that their previous efforts to interrogate the governing variables informing decision-making have failed to yield the desired results, and when they are (ii) motivated to engage in deeper reflexivity before they act. Since *a priori* knowledge connotes active engagement, it can extend our knowledge beyond immediate sensory experience, for example, by prompting questions about 'what else might be known?' rather than merely 'what is known' (see also Suddaby, 2014). Therefore, managers can choose to evaluate the appropriateness of ends themselves (processual shift 2). While teleological epistemic motivation (*after* the fact) can equally be applied in the absence of Gen-AI (as depicted in the baseline model), managers on the path toward epistemic up-skilling can harness Gen-AI as a way to close the explanatory gap between what *is* (i.e., what they feel they can explain *now* by activating their reflexivity), and what they *might be able to* explain in future if the situation at hand is carried to its full (reflexive) potential (Dewey, 1916). This type of development is triggered by the unsatisfactory nature of the 'explanations' returned by Gen-AI (Sarkar, 2024), vis-à-vis a manager's current understanding of a situation. This discrepancy forces managers to ask why they are dissatisfied with explanations provided by Gen-AI in light of their current understanding of a situation.

This shift to activate reflexivity can be elaborated as a sequence of three steps, all of which can be subsumed under the broader pattern of managers making use of Gen-AI's explanatory silence[5]. First, managers turn to Gen-AI for 'advice', although said advice will lack moral insight or context sensitivity in the phronetic sense when managers are struggling to make sense of a novel situation (e.g., when individuals experience puzzlement in the absence of prior

[5] Note that these elaborations relate to, and successively build upon, each other. In isolation or out of sequence, we doubt that our theorizing about managers using Gen-AI to activate and develop reflexivity will hold. Equally crucial, in the up-skilling pathway, there is only one processual shift (no. 2 in Figure 2a) in the model influenced by Gen-AI. That means that the logic of the baseline model (Figure 1), including the role of *a priori* knowledge and general epistemic motivation, applies in the up-skilling path too.

direct experience - see Rousseau, 2020 for a Covid-related example). Conversely, when results align with or exceed expectations, indicating sufficient competence, individuals consult Gen-AI to interrogate their judgments or generate creative variations (Choudhary, Marchetti, Shrestha & Puranam, 2025). In both instances, managers can ask a Gen-AI tool to produce synthetic outputs (e.g., potential scenarios/solutions) drawn from its large corpus of codified experiences. For instance, Onder and Uzun (2021) have shown that managers used AI-driven decision tools to model business scenarios during the early phases of the COVID-19 pandemic. More broadly, in this first step of the processual shift, managers use Gen-AI to generate alternative contexts and moral situations to enhance their own reflexivity.

Second, managers probe such Gen-AI outputs by eliciting explanations from Gen-AI, even though these are often generic, with little contextual nuance (Balasubramanian et al., 2020; Smith, 2019). While humans are motivated to "understand the goals, social intent, contextual awareness, task limitations, [and] analytical underpinnings . . . of the system in an attempt to verify its trustworthiness" (Lyons, Clark, Wagner & Schuelke, 2017: 37), AI models are less adept in this respect (Cornelissen, Höllerer, Boxenbaum, Faraj et al., 2024; Sarkar, 2024). Such explanations can be useful for promoting critical thinking (Larson et al., 2024), but not for understanding the model *per se* (Sarkar, 2024). Interestingly, recent empirical studies of "chain-of-thought" reasoning show that such outputs often simulate, but do not possess, actual reasoning capacity and fail once problem complexity exceeds a specific threshold (Shojaee, Mirzadeh, Alizadeh, Horton et al., 2025). When these illusions unravel and Gen-AI outputs fail unexpectedly, users face an explanatory void. This limitation then forces managers to supply their own explanations to bridge gaps between past experiences and future possibilities concerning moral insights, contextual sensitivity and practical know-how.

Third, by engaging with Gen-AI's explanatory silence, while trying to understand a concrete situation, managers further enhance their reflexive thinking, developing plausible explanations to guide their own behavior, for instance, by way of the 5 why-test (Serrat, 2017).

This test helps close the gap between generic and context-sensitive reasoning. When managers are dissatisfied with results, repeatedly questioning prompts them to reflect more deeply on the assumptions that underpin their decisions (Argyris, 2002). Thus, asking Gen-AI 'why' (in relation to a specific problem over multiple iterations) in light of superficial AI outputs can activate managers' own judgment. Yang, Banovic and Zimmerman (2018) cite the example of a designer using Gen-AI. By presenting diverse and unexpected outputs, AI prompted the designer to question their initial assumptions and explore new creative directions. Similarly, managers engaged in hiring staff may receive plausible but context-insensitive AI-generated justifications, leading them to reassess outcomes using their own judgment (Binns et al., 2018). In a research context, it has been argued that "a researcher creatively draws in additional substantive theoretical assumptions and ideas that, configured into an inferential line of reasoning, go beyond the codified priors and thus expand and refine our [contextual] knowledge of phenomena" (Cornelissen et al., 2024: 4). Similarly, Mittelstadt, Russell and Wachter (2019) have found that managers in healthcare settings use AI risk assessments as the starting point for integrating additional, context-specific knowledge. This suggests that a purposive use of Gen-AI explanations can stimulate phronesis.

What we refer to as the 'booster effect' of epistemic up-skilling arises in the presence of Gen-AI through this sequence of three steps. For the three components of phronesis (see also Table 1), this means that the booster effect deepens (i) moral insight when AI outputs provoke ethical interrogation of alternative courses of action (Mittelstadt et al., 2019); (ii) contextual sensitivity when managers contrast generalized AI framings with the situated particulars of the case at hand (Moser, Glaser & Lindebaum, 2023); and (iii) practical know-how when Gen-AI augments reflexive experimentation, scenario testing and post-hoc evaluation while leaving situated enactment to the manager (Onder & Uzun, 2021).

Thus, far from undermining phronesis, our model (Figure 2b) highlights a processual shift that can help to foster phronesis. The preceding arguments account for the booster effect in

Figure 2b, which kicks in after managers have exhausted their own reflexive abilities and turned to Gen-AI, and leveraging its explanatory silence to augment their reflexivity. The green double arrow builds on the baseline model, and each iteration boosts managerial phronesis vis-à-vis its preceding level[6], as indicated in Figure 2b through the reference to Time 1 and Time 2+n. Crucially, the up-skilling path requires that a modicum of managerial experience and expertise is already in place when engaging with Gen-AI outputs – a verifying anchor in first-hand experience is need for up-skilling to occur. In other words, up-skilling from an experiential 'blank sheet' is unlikely in our view, and that applies to moral insights, contextual sensitivity and practical know-how alike. In sum, epistemic de-skilling and up-skilling result from managers either cognitively offloading to, or reflexively engaging with, Gen-AI at work. Next, we theorize the boundary conditions that determine when de-skilling and up-skilling are more likely to occur.

BOUNDARY CONDITIONS FOR EPISTEMIC DE-SKILLING AND UP-SKILLING

When are managers most likely to drift into epistemic de-skilling, or, conversely, to engage in epistemic up-skilling, we theorize, depends upon two boundary conditions that influence the processual shifts in our models, and how these in turn shape the likelihood and direction of epistemic skill development: perceived time pressure (facilitating de-skilling) and perceived and formal accountability (facilitating up-skilling). Although additional boundary conditions may exist, these two represent particularly consequential contingencies for understanding when epistemic de or up-skilling is likely to happen. Identifying boundary conditions is key to delineate the scope of our theorizing and help clarify when processual shifts foster either epistemic de or up-skilling concerning managerial phronesis. Considering our model as starting

[6] Note that the logic concerning the booster effect, as just highlighted, differs from the inhibitor effect. The Gen-AI inhibitor effect builds upon the baseline model in the *absence* of individual self-effort, and this is why the red double arrow grows longer with each iteration of cognitive offloading. The green double-arrow that indicates the booster effect is shorter than the red double-arrow of the inhibitor effect, because epistemic up-skilling requires individual effort first to develop phronesis. Each iteration builds on the preceding level. Hence, the booster effect works successively, building on the progress of the previous iteration.

the conversation around possible boundary conditions, we focus on the high (rather than low) ends of these conditions. We argue that this yields the greatest theoretical dividends, while avoiding unnecessary complexity in the model.

Boundary condition 1: perceived time pressure

The first important boundary condition is perceived time pressure – the perception that insufficient time is available to complete required tasks (Maruping, Venkatesh, Thatcher & Patel, 2015), especially when task completion requires social interaction with colleagues (Osterman, Kochan, Locke & Piore, 2001). Perceived time pressure is particularly salient in organizational contexts characterized by continuous performance monitoring. Such conditions are common in tightly coupled and high-velocity environments, including logistics and distribution, call-center operations, financial trading, construction and emergency healthcare, where real-time metrics structure daily work. Time pressure also arises in professional service and knowledge-intensive settings, such as consulting, law, accounting, and software development, where productivity is monitored through billable hours, milestone tracking, and deadline-driven project management (Perlow, 1999). Across these sectors, the combination of measurable outputs, digitalized monitoring systems, and norms emphasizing efficiency makes perceived time pressure a structurally embedded feature of managers' task environments.

Perceived time pressure affects the processual shifts 1a and 1b in Figure 2a because it directs epistemic engagement away from creating new experience (processual shift 1a). This is due to the cognitive effort to activate one's creativity under conditions least favorable for such activation (i.e., time pressure). Prior research makes the case that time pressure can limit cognitive resources needed for creative work (Roskes, 2015). As to processual shift 1b, time pressure can trigger the avoiding first-hand experience when Gen-AI serves as a reference point rather than learning by 'walking around'. This avoidance may be driven by the possibility that learning by 'walking around' involves the potentially challenging task of working with others to find a solution to a given problem, including overcoming initial disagreements and tensions as to the best way forward. Therefore, what both shifts have in common is an ‘avoidance’ motivation (Zajonc, 1980), which, if exercised, leads to reduced opportunities to develop all three components of phronesis: moral insight, contextual sensitivity, and practical know-how.

These junctures are inherently time-consuming for managers, and under perceived time pressure, both generating new experiences and taking time to diagnose a problem before solving it become less appealing, given the amount of cognitive effort and time required for deeper problem-solving (León-Domínguez, 2024). Consistent with this argument, Shalvi, Eldar and Bereby-Meyer (2012) find that under time pressure, people tend to serve their self-interests, since overcoming this tendency requires people to exert self-control, something that is harder to do under time pressure.

Boundary condition 2: perceived and formal accountability

The second important boundary condition for our theory is accountability, defined as the “expectation that one may be called on to justify one’s beliefs, feelings, and actions to others” (Lerner & Tetlock, 1999: 255). Accountability operates both prospectively, through the anticipation of being evaluated, and retrospectively, through post-hoc justification when a manager is being called upon to justify current or past decisions. Accountability pressures are especially pronounced in task environments where decisions are consequential, visible, and routinely subject to oversight. These include public-sector and regulatory settings (e.g., courts, policing, healthcare), financial and professional services (e.g., auditing, consulting), and safety-critical industries (e.g., aviation, energy, pharmaceuticals), where formal evaluation and justification requirements are institutionalized (Power, 1997). Accountability is traditionally also salient in education and research, where human assessment and peer-review is integral to the profession, albeit that argument is, ironically, being challenged in education and research alike through the presence of Gen-AI (Lindebaum, Nolan, Ashraf, Islam et al., 2025).

Following Lerner and Tetlock (1999), we distinguish between perceived accountability, which reflects a manager’s subjective sense of being answerable to others, and formal accountability, embedded in organizational rules, oversight structures, and evaluation systems. This distinction widens the applicability of accountability as a boundary condition beyond structurally regulated roles, making it both relevant to a wider set of managers, and to managerial phronesis more specifically. This is because the perception of accountability ties managers to a concrete social situation in which they have a stake, which, in turn, triggers moral and contextual judgments about how to act now to obtain a desirable future result. Consequently, processual shift 2 is characterized by an 'approach motivation' (Zajonc, 1980).

Under such conditions, Gen-AI's inability to supply possible explanations becomes generative rather than limiting, precisely because the system cannot justify decisions in the way that a manager with a long-term interest in phronesis might be able to do. For this reason, Gen-AI's explanatory silence can compel managers to actively reconstruct the rationale themselves. Thus, in such contexts, managers can possibly benefit from actively mobilizing Gen-AI's lack of explanation in order to cultivate deeper reflexivity, which ultimately yield the moral insight and contextual sensitivity that are characteristic of phronesis.

DISCUSSION

In this article, we asked *why, how, and under which conditions Gen-AI affects the development of managerial phronesis.* Asking these questions matters because phronesis is increasingly vital in a world marked by uncertainty, complexity, and competing demands on managerial decision-making (Shotter & Tsoukas, 2014), while Gen-AI only offers synthetic substitutes for first-hand experience. Thus, our first aim was to develop a baseline process model to explain how managers can develop phronesis in the absence of Gen-AI. We introduced conceptual innovations that explore the unique characteristics of human learning in the real world, such as the mutual causality between *a priori* knowledge and general epistemic motivation, and use this interplay to explain how managers can mobilize their agency to develop managerial phronesis. These innovations were essential to better explain why and how the arrival of Gen-AI affects the development of phronesis.

Given that Gen-AI is an epistemic technology (Alvarado, 2023) producing synthetic content, our second aim was to theorize processual shifts (see Figures 2a & 2b), influenced by the boundary conditions of perceived time pressure (fostering epistemic de-skilling), as well as perceived and formal accountability (fostering epistemic up-skilling), through which Gen-AI affects the development of managerial phronesis. Of note, our focus on managerial phronesis does more than interpret the cognitive implications of Gen-AI; it exposes the epistemic, ethical, and situational trade-offs that accompany the integration of Gen-AI into managerial learning at work. We now formulate three distinctive theoretical contributions to management research and practice, and close with directions for future research.

Theoretical contributions

Our first theoretical contribution concerns several conceptual innovations to the process of developing managerial phronesis. In particular, our conceptualization of the mutual causality between *a priori* knowledge and general epistemic motivation points to a shift toward prospective learning and continuously expanding managerial phronesis. The baseline model maps the entire process from pre-experience to post-experience, showing how experiential learning aids the continuous expansion of managerial phronesis when managers seek to activate their own reflexivity (i.e., when managers exercise agency). That means the reflexive-phronetic nexus remains a fundamental human advantage in knowledge creation, distinguishing true learning in concrete social situations from the production of codified information by Gen-AI. Although Gen-AI is powerful at reassembling existing data (Smith, 2019), it is constrained by the boundaries of its training data and objective functions. Gen-AI cannot genuinely reframe a problem or question its own ends in the way a reflexive human mind can (Zimmer, Vassilakopoulou, Grisot & Niemimaa, 2024). What Currie and Kerrin (2004: 10) refer to as "information epistemology" implies that Gen-AI excels at codifying and retrieving data, but is itself less able (and potentially unable) to pose deeper axiomatic know-why or know-how questions that humans, when committed to the time and space they inhabit, could. In so doing, our model adds to our understanding of the process of how managerial phronesis develops.

However, our conceptual innovations have broader theoretical ramifications beyond the immediate scope of the baseline model (Figure 1). For example, scholars who study organizational routines think about the motivation (the know-why: Dittrich & Seidl, 2018), implementation (the know-how: Howard-Grenville, 2005), and constitution (the know-that: Sele & Grand, 2016) of possible future routines. In the absence of new stimuli, routines can become static and possibly dysfunctional—no longer able to produce desirable results when situations change. Our baseline model is relevant here, because it explains how the mutual causality between *a priori* knowledge and general epistemic motivation can prompt managers to consider changing routines *before* external forces disrupt them. *After* a routine is disrupted, due to, for example, changes in the organizational environment, our model suggests that the effectiveness of any new routines developed in response to such changes will depend on the teleological epistemic motivation of managers and their reflexive interrogation of the governing variables that underpin decision-making. This reflexive capacity is central to phronesis; it engenders discerning judgment rooted in context, experience, and ethical reasoning, instead of mere adherence to technical recommendation (Flyvbjerg, 2001). Furthermore, managers with a capacity for phronesis are more likely to ask *why* and *how* routines should be altered when the need arises, not just *what* should be changed. Such managers foster long-term adaptive capability, rather than short-term optimization. In addition to guiding routine modifications, phronesis can influence whether such adaptations reinforce or deplete the epistemic agility required for sustained managerial learning (Balasubramanian et al., 2020).

Our second contribution lies in theorizing the processual shifts through which Gen-AI affects the process of developing managerial phronesis, as well as the boundary conditions that shape these dynamics. Specifically, we explain how shifts in the learning process can generate epistemic de-skilling, whereby reliance on Gen-AI diminishes individuals' cognitive effort and judgment, and epistemic up-skilling, whereby engagement with Gen-AI prompts deeper reflexivity and strengthens judgment capabilities. Relevant here is our identification of the boundary conditions under which Gen-AI produces these divergent outcomes, namely, perceived time pressure (fostering de-skilling), and both perceived and formal accountability (fostering up-skilling). By examining Gen-AI's temporal dynamics, as represented in multiple feedback loops (see Figures 2a & 2b), our theorizing shows how Gen-AI can exert progressively negative effects on managerial phronesis through de-skilling, as well as progressively positive effects through up-skilling.

One way to exemplify the progressive outcomes of de- and upskilling is by way of studies on work design (Parker & Grote, 2022). This is because perceived time pressure is produced by work design that compresses decision cycles and prioritizes speed, under which Gen-AI displaces epistemic engagement and triggers de-skilling. Interestingly, recent empirical studies suggest that the use of Gen-AI may help workers to complete tasks faster, assume a wider range of tasks, and expand work into more working hours during the day. Unsurprisingly, the downside is that workers are confronted with a growing workload that stretches their ability to juggle multiple tasks at the same time. This results into "cognitive fatigue, burnout, and weakened decision-making", ultimately yielding "lower quality work, turnover, and other problems" (Ranganathan & Ye, 2026). Work design also matters for the attribution of perceived and formal accountability. In the case of perceived accountability, work design is pertinent because it is concerned with "content and organization of one's work tasks, activities, relationships, and [also perceived] responsibilities" (Parker, 2014: 662). As to formal accountability, work design helps render managerial judgment visible and reviewable. Both perceived and formal accountability thereby help enable epistemic engagement toward up-skilling through how work design is configured at work. Thus, "work design emerges as a crucial concept for helping to anticipate and mitigate uncertainties and challenges" caused by the integration of Gen-AI at work (Parker, Trezise & Thomas, 2025: 15).

In relation to up-skilling, the theoretical significance of reflexively interrogating the governing variables that underpin decision-making (or teleological epistemic motivation) *after the fact* indicates that up-skilling is more relevant for tasks with meta-cognitive connotations. Such tasks require "thinking about thinking" or the "monitoring and control of thought" (Martinez, 2006: 696), both in terms of accountability being activated retrospectively and prospectively. The question is how much actual 'headspace' is permitted for managers at work to engage in meta-cognitive contemplation in relation to their perceived and formal accountability, given that work intensification has been documented as a result of Gen-AI use at work (Ranganathan & Ye, 2026). Further, incentives that are measurable digitally, such as 'worker productivity scores' (see Kantor & Sundaram, 2022), conflate output with more meta-cognitive performance as to the why and how behind purpose, processes, and tasks. Consequently, when meta-cognitive probing becomes less likely, so do the possible benefits of epistemic up-skilling. Finally, it is crucial to recognize that emerging empirical evidence on Gen-AI and learning points more readily toward de-skilling rather than up-skilling (Fan, Tang, Le, Shen et al., 2025; Lee, Sarkar, L., Drosos et al., 2025). Although Gen-AI may improve the speed and volume of task completion in some analytical and creative domains, the same cannot yet be said for complex managerial tasks that depends on situated judgement (Dell'Acqua et al., 2026). Crucially, task completion is not tantamount to knowledge gains in terms of knowing-why and knowing-how (Fan et al., 2025), and ignoring this point will turn into a cost for organizations when routines and workflows are disrupted. This point raises deeper developmental concerns as Gen-AI becomes embedded in the workplace, thereby shaping first-hand experience through which expertise and phronesis develop. One might say that one needs to be an established expert first (pre-arrival Gen-AI) to harness the benefits of Gen-AI to develop expertise and phronesis further. However, for junior managers now socialized into the use of Gen-AI, it appears questionable if they have the ability to develop such expertise and phronesis in the first place given the organizational expectations to use the technology

(Ranganathan & Ye, 2026). Thus, to make epistemic up-skilling possible, it requires rethinking agency and first-hand experience in AI-mediated settings as experience that continues to preserve active judgement, reflexive engagement and meaningful exposure to the situations from which managerial phronesis emerges. This further sharpens our focus on reflexivity and teleological epistemic motivation.

Finally, our third contribution involves the development of a process perspective (Cloutier & Langley, 2020), which makes it possible to analyze how the dynamic interplay between human experience and Gen-AI produces epistemic outcomes through epistemic de - and up-skilling. A process perspective implies a focus on becoming rather than being (Hay, 2023). It emphasizes how learning evolves over time through continuous interactions between managers, technology, and the environment (see the multiple feedback loops in each model). This contrasts with static perspectives, when the relationship between two variables is 'frozen in time' and considered a valid fact over time (see Guba & Lincoln, 1994). In this sense, the processes of epistemic de - and up-skilling can reconfigure the phronesis of managers as digitally mediated learning emerges through Human-AI interactions. In this respect, both the inhibitor (concerning epistemic de-skilling) and booster effects (concerning epistemic up-skilling) are of particular interest, because they foreshadow the likely costs or benefits of organization denying or enabling managers to develop their phronesis. At the same time, our model can be modified to include other epistemic outcomes, including critical thinking (Larson et al., 2024) and creativity (Amabile, 2019; Cronin & Loewenstein, 2018). Therefore, our models have conceptual versatility beyond the immediate scope of managerial phronesis. As detailed below, this versatility may be quite important for future research.

Implications for future research

Building on the three contributions discussed above, we identify two areas for future research. First, although the training and adaptation of Gen-AI systems lie outside the scope of this article, our models raise an important question about the epistemic quality of managerial knowledge that may later be codified into such systems. As organizations increasingly use approaches, such as retrieval-augmented generation (RAG), Gen-AI systems are often anchored in organizational sources treated as 'ground truth' (Yu, Gan, Zhang, Tong et al., 2025). If these sources are themselves generated through epistemically de-skilled managerial work, they may carry forward impoverished forms of moral insight, contextual sensitivity, and practical know-how. The risk, then, is not only that Gen-AI contributes to managerial de-skilling, but that de-skilled managerial outputs become inputs for future Gen-AI systems, creating recursive feedback loops of human and machine de-skilling (Hannigan, McCarthy & Spicer, 2024).

Further risks emerge when AI models are heavily customized to reflect a user's prior choices, preferences, or inferred values (given their continuous learning from data). Over time, such customization can generate a type of epistemic mirroring, much like echo chambers in social media, where outputs reinforce the user's existing beliefs, rather than challenging them. Recent empirical studies lend to support to this caution (Glickman & Sharot, 2025). When human and AI 'beliefs' (if they can be called that) begin to converge in this way over time (Eicke et al., 2025), the scope for critical interrogation narrows, leading to diminished opportunities for up-skilling, even among users who are otherwise motivated to learn. Over time, we may observe an accumulative effect, where all acts of cognitive offloading widen the gap between what managers know and what managers could have known, had they resisted offloading. Even for managers who are interested in up-skilling, it will become more difficult to close the gap. As Kostick-Quenet (2025) warns, "without careful deliberation, customized AI systems [e.g., personalized AI in healthcare and other high-stakes domains] can compromise the diversity and reach of human knowledge by restricting exposure to critical information that may conflict with users' preferences and biases" (p. 1). Importantly, this dynamic also raises a broader organizational research agenda, such as the need for future work to examine how epistemic patterns become institutionalized through routines, decision protocols, and accountability structures, potentially transforming localized tendencies toward de-skilling or up-skilling into durable features of managerial learning. It is through these pathways of institutionalization that the epistemic consequences of Gen-AI for managers may scale into persistent organizational capabilities (or vulnerabilities - see Gerlach & Lange, 2026).

Second, the ultimate theoretical benefit of our models resides in their conceptual versatility. Their processual orientation—with or without the presence of Gen-AI— can serve as a scaffold, which supports a wide variety of cognitive, ethical, or social phenomena. The models are open to multiple endpoints beyond phronesis. Consequently, they allow researchers to investigate a range of different outcomes, while maintaining analytic coherence across the same processual architecture, including the processes of epistemic de - and up-skilling. For instance, the theoretical flexibility of our model makes it possible to consider other epistemic outcomes, such as critical thinking (Larson et al., 2024) and creativity (Amabile, 2019; Cronin & Loewenstein, 2018). Critical thinking—in the sense of being able to manage cognitive biases and engage in objective situational analyses, combined with an ability to reflect on and challenge prevailing social norms (Larson et al., 2024)—could be examined by analyzing how synthetic inputs, model formalization, and user uptake enable or thwart such thinking. As for the creative process, briefly defined as the ability to change existing perspectives (Cronin & Loewenstein, 2018), our baseline model explains how existing perspectives can be modified by activating the mutual causality between *a priori* knowledge and general epistemic motivation. Just as not all roses are red, it may be possible to imagine alternative uses for a Ziploc bag beyond food storage. Yet, as Cronin and Loewenstein (2018) suggest, envisioning such alternatives is often curtailed by entrenched mental models. In this context, Gen-AI presents a double-edged tool for creativity. On the one hand, its ability to draw on vast synthetic datasets allows it to possibly generate novel associations and uses (within the limits of its training data) that may fall outside the user's habitual frame. On the other hand, reliance on such outputs may reinforce default patterns—unless users actively interrogate and reshape them.

Looking ahead, given theoretical concerns about cognitive offloading (León-Domínguez, 2024) and critical thinking (Larson et al., 2024) in the age of Gen-AI, we need to know whether such concerns are (dis)confirmed by empirical studies, albeit emerging studies do appear to confirm this concern (Fan et al., 2025; Lee et al., 2025). As of now, questions arise about the state of empirical research that advocate the use of Gen-AI to boost learning (Horvath, 2025). Hence, it requires explicit emphasis that the pathway for epistemic up-skilling only works due to the limitations of Gen-AI in explaining its reasoning behind outputs. Managers might use Gen-AI to bridge explanatory voids between the continuing collection of first-hand experiences, and that which they do not know yet. Yet, this will be cognitive taxing for individuals, and it is not clear if this can happen at scale. There is thus need for rigorously designed empirical studies to ensure that the next iteration of theorizing is built on a solid foundation. Otherwise, we run the risk "building theory upon theory rather than empirical validation" (Prasad, 2023: 1259).

Practically speaking, our model serves as a possible blueprint for organizational interventions designed to (i) boost phronesis without Gen-AI (see Figure 1), and with Gen-AI (by way of epistemic up-skilling, see Figure 2b) and (ii) prevent the decline in managerial phronesis (by way of epistemic de-skilling, see Figure 2a). In the absence of Gen-AI, phronesis can be developed by instilling managerial sensitivity to the mutual causality between *a priori* knowledge and general epistemic motivation *before* the fact, alongside a focus on teleological epistemic motivation *after* the fact (by way of reflexivity). In the presence of Gen-AI, theorizing processual shifts and recognizing the boundary conditions in the baseline model can help us understand how to avoid de-skilling and foster up-skilling. Both *before* and *after* the fact, interventions can be designed to increase a manager's access to useful and usable knowledge (Aguinis & Cronin, 2022).

CONCLUSION

To conclude, our process models advance both our substantive understanding of how managerial phronesis can be developed in the absence of Gen-AI, but also why and how Gen-AI can both undermine (via epistemic de-skilling) and boost (via epistemic up-skilling) managerial phronesis given the boundary conditions discussed. In doing so, we contribute to emerging conversations on human–AI interaction by showing that Gen-AI does not merely affect managerial efficiency or decision quality, but may fundamentally reshape the experiential and social foundations through which managers develop moral judgment, contextual sensitivity, and practical wisdom over time. Given the rapid diffusion of Gen-AI into organizational contexts that increasingly require precisely these forms of judgment, understanding its implications for managerial phronesis is both theoretically consequential and practically urgent. We hope that our models will spark new lines of theoretical inquiry, alongside much-needed empirical testing, into the ways that Gen-AI shapes the development of managerial phronesis, and other phenomena, at work.

REFERENCES

Adler, M. J., & van Doren, C. 1940/1972. ***How to read a book - the classic guide to intelligent reading***. New York: Touchstone.

Aguinis, H., & Cronin, M. A. 2022. It's the Theory, Stupid. ***Organizational Psychology Review***.

Alon-Barkat, S., & Busuioc, M. 2022. Human–AI interactions in public sector decision making: "Automation bias" and "selective adherence" to algorithmic advice. ***Journal of Public Administration Research and Theory***, 33(1): 153-169.

Alvarado, R. 2023. AI as an Epistemic Technology. ***Science and Engineering Ethics***, 29(5): 32.

Amabile, T. M. 2019. Creativity, Artificial Intelligence, and a World of Surprises. ***Academy of Management Discoveries***, 6(3): 351-354.

Amershi, S., Weld, D., Vorvoreanu, M., Fourney, A., Nushi, B., Collisson, P., Suh, J., Iqbal, S., Bennett, P. N., & Inkpen, K. 2019. ***Guidelines for human-AI interaction***. Paper presented at the Proceedings of the 2019 chi conference on human factors in computing systems.

Ames, M. C. F. D. C., Serafim, M. C., & Zappellini, M. B. 2020. Phronesis in administration and organizations: A literature review and future research agenda. ***Business Ethics: A European Review***, 29: 65-83.

Antonacopoulou, E. P. 2010. Making the Business School More 'Critical': Reflexive Critique Based on Phronesis as a Foundation for Impact. ***British Journal of Management***, 21(s1): s6-s25.

Antonacopoulou, E. P., Bento, R., Edward, G., Hawkins, B., Moldjord, C., Rigg, C., Sklaveniti, C., Soh, W. G., & Stokkeland, C. C. 2023. Collaborative inquiry fuelled by reflexive learning: changing change. ***The Journal of Applied Behavioral Science***, 59(4): 740-777.

Arendt, H. 1958/1985. ***The Human Condition***. Chicago: Chicago University Press.

Argyris, C. 1982. ***Reasoning, Learning and Action: Individual and Organizational***. San Francisco, CA: Josey-Bass, Inc.

Argyris, C. 2002. Double-Loop Learning, Teaching, and Research. ***Academy of Management Learning & Education***, 1(2): 206-218.

Balasubramanian, N., Ye, Y., & Xu, M. 2020. Substituting Human Decision-Making with Machine Learning: Implications for Organizational Learning. ***Academy of Management Review***, 47(3): 448–465.

Bergenholtz, C., Vuculescu, O., Günzel-Jensen, F., & Frederiksen, L. 2026. Leveling up or Leveling Down? The Impact of Generative AI on Student Performance in Business Schools. ***Academy of Management Learning & Education***.

Binns, R., Kleek, M. V., Veale, M., Lyngs, U., Zhao, J., & Shadbolt, N. 2018. 'It's Reducing a Human Being to a Percentage': Perceptions of Justice in Algorithmic Decisions, ***Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems***: Paper 377. Montreal QC, Canada: Association for Computing Machinery.

Brown, O., Davison, R. M., Decker, S., Ellis, D. A., Faulconbridge, J., Gore, J., Greenwood, M., Islam, G., Lubinski, C., MacKenzie, N. G., Meyer, R., Muzio, D., Quattrone, P., Ravishankar, M. N., Zilber, T., Ren, S., Sarala, R. M., & Hibbert, P. 2024. Theory-Driven Perspectives on Generative Artificial Intelligence in Business and Management. ***British Journal of Management***, 35(1): 3-23.

Chan, C. K. Y. 2022. ***Experiential learning theories and frameworks, Assessment for Experiential Learning***. London: Routledge.

Charland, L. C. 2011. Moral Undertow and the Passions: Two Challenges for Contemporary Emotion Regulation. ***Emotion Review***, 3(1): 83-91.

Choudhary, V., Marchetti, A., Shrestha, Y. R., & Puranam, P. 2025. Human-AI Ensembles: When Can They Work? ***Journal of Management***, 51(2): 536-569.

Clay, G., Mlynski, C., Korb, F. M., Goschke, T., & Job, V. 2022. Rewarding cognitive effort increases the intrinsic value of mental labor. ***Proceedings of the National Academy of Sciences***, 119(5): e2111785119.

Cloutier, C., & Langley, A. 2020. What Makes a Process Theoretical Contribution? ***Organization Theory***, 1(1): 1-32.

Coeckelbergh, M. 2020. ***AI ethics***. Cambridge, MA: MIT Press.

Contu, A. 2023. Antigone: On Phronesis and How to Make Good and Timely Leadership Decisions. ***Academy of Management Review***, 48(1): 149-164.

Cornelissen, J., Höllerer, M. A., Boxenbaum, E., Faraj, S., & Gehman, J. 2024. Large Language Models and the Future of Organization Theory. ***Organization Theory***, 5(1): 1-15.

Cronin, M. A., & Loewenstein, J. 2018. ***The craft of creativity***. Stanford, CA: Stanford University Press.

Cunliffe, A. L. 2016. "On Becoming a Critically Reflexive Practitioner" Redux:What Does It Mean to Be Reflexive? ***Journal of Management Education***, 40(6): 740-746.

Currie, G., & Kerrin, M. 2004. The Limits of a technological fix to knowledge management: Epistemological, political and cultural issues in the case of intranet implementation. ***Management Learning***, 35(1): 9-29.

de Boer, B., Hoek, J., & Kudina, O. 2018. Can the technological mediation approach improve technology assessment? A critical view from 'within'. ***Journal of Responsible Innovation***, 5(3): 299-315.

Dell'Acqua, F., McFowland, E., Mollick, E., Lifshitz, H., Kellogg, K. C., Rajendran, S., Krayer, L., Candelon, F., & Lakhani, K. R. 2026. Navigating the Jagged Technological Frontier: Field Experimental Evidence of the Effects of Artificial Intelligence on Knowledge Worker Productivity and Quality. ***Organization Science***, 37(2): 403-423.

Deresiewicz, W. 2023. Why AI Will Never Rival Human Creativity - Predictive mechanisms preclude the originality needed for true art. ***Retrieved from https://www.persuasion.community/p/why-ai-will-never-rival-human-creativity on 23 June 2023***.

Dewey, J. 1916. ***Essays in experimental logic***. Chicago, IL: University of Chicago Press.

Dewey, J. 1922. ***Human Nature and Conduct***. New York, NY: Henry Holt and Company.

Dierksmeier, C., Habisch, A., & Bachmann, C. 2018. Practical wisdom: Management's no longer forgotten virtue. ***Journal of Business Ethics***, 153(1): 147-165.
Dittrich, K., & Seidl, D. 2018. Emerging intentionality in routine dynamics: A pragmatist view. ***Academy of Management Journal***, 61(1): 111-138.
Eicke, A.-K., Foege, J. N., & Nüesch, S. 2025. Iterative Alternative Evaluation within Human–Artificial Intelligence Problem-Solving: An Extension to Raisch and Fomina's "Combining Human and Artificial Intelligence". ***Academy of Management Review***, 50(2): 480-481.
Eisikovits, N., & Feldman, D. 2022. AI and Phronesis. ***Moral Philosophy and Politics***, 9(2): 181-199.
Fan, Y., Tang, L., Le, H., Shen, K., Tan, S., Zhao, Y., Shen, Y., Li, X., & Gašević, D. 2025. Beware of metacognitive laziness: Effects of generative artificial intelligence on learning motivation, processes, and performance. ***British Journal of Educational Technology***, 56(2): 489-530.
Faraj, S., & Pachidi, S. 2021. Beyond Uberization: The co-constitution of technology and organizing. ***Organization Theory***, 2(1): 1-14.
Flyvbjerg, B. 2001. ***Making social science matter [electronic book] : why social inquiry fails and how it can succeed again / Bent Flyvbjerg ; translated by Steven Sampson***: Oxford, UK ; Cambridge University Press, 2001.
Forgas, J. P. 1985. ***Interpersonal behaviour: The psychology of social interaction***. Sydney & Oxford: Pergamon Press.
Friedland, J. 2019. Activating Moral Agency by Design: A Model for Ethical AI Development. ***MIT Sloan Management Review***, Summer Issue: 1-7.
Gadamer, H. G. 2004. ***Truth and Method***. London: Sheed and Ward Stagbooks.
García-Peñalvo, F., & Vázquez-Ingelmo, A. 2023. What Do We Mean by GenAI? A Systematic Mapping of The Evolution, Trends, and Techniques Involved in Generative AI. ***International Journal of Interactive Multimedia and Artificial Intelligence***, 8(4): 7-16.
Gerlach, J. P., & Lange, D. 2026. Fading Memories: The Role of Machine Learning in Organizational Knowledge Depreciation. ***Academy of Management Review***.
Glaser, V. L., Sloan, J., & Gehman, J. 2024. Organizations as Algorithms: A New Metaphor for Advancing Management Theory. ***Journal of Management Studies***, 61: 2748-2769.
Glickman, M., & Sharot, T. 2025. How human–AI feedback loops alter human perceptual, emotional and social judgements. ***Nature Human Behaviour***, 9(2): 345-359.
Guba, E. G., & Lincoln, Y. S. 1994. Competing paradigms in qualitative research. In N. K. Denzin, & Y. S. Lincoln (Eds.), ***Handbook of qualitative research***: 105-117. Thousand Oaks: Sage.
Guile, D., & Popov, J. 2025. Machine learning and human learning: a socio-cultural and-material perspective on their relationship and the implications for researching, working and learning. ***AI and Society***, 40: 325-338.
Hannigan, T., McCarthy, I. P., & Spicer, A. 2024. Beware of Botshit: How to Manage the Epistemic Risks of Generative Chatbots. ***Business Horizons***, 67(5): 471-486.
Hay, A. 2023. On the Neglect of Fallibility in Management Learning and Education: From Perfect to Adequate Managers. ***Academy of Management Learning & Education***, 22(4): 702–717.
Hibbert, P., & Cunliffe, A. 2015. Responsible Management: Engaging Moral Reflexive Practice Through Threshold Concepts. ***Journal of Business Ethics***, 127(1): 177-188.
Holt, R., & Zundel, M. 2023. ***The poverty of strategy : organization in the shadows of technology***. Cambridge, UK: Cambridge University Press.
Horvath, J. C. 2025. ***The Digital Delusion: How Classroom Technology Harms Our Kids' Learning—and How to Help Them Thrive Again***. Scottsdale, AZ: LME Global.

Howard-Grenville, J. A. 2005. The persistence of flexible organizational routines: The role of agency and organizational context. ***Organization Science***, 16(6): 618-636.
Jordon, J., Szpruch, L., Houssiau, F., Bottarelli, M., Cherubin, G., Maple, C., Cohen, S. N., & Weller, A. 2022. Synthetic Data - what, why and how? ***Report by the The Royal Society retrieved from https://royalsociety.org/-/media/policy/projects/privacy-enhancing-technologies/Synthetic_Data_Survey-24.pdf on the 2nd of October 2025***.
Kant, I. 1781/2007. ***Critique of Pure Reason (Trans. Marcus Weigelt (based on the translation of Max Muller)***. London: Penguin.
Kantor, J., & Sundaram, A. 2022. The Rise of the Worker Productivity Score. ***New York Times***, Retrieved from https://www.nytimes.com/interactive/2022/08/14/business/worker-productivity-tracking.html on 9 September 2022.
Kelly, G. A. 1955. ***The Psychology of Perssonal Constructs***. New York: Norton.
Kemp, A. 2024. Competitive Advantage Through Artificial Intelligence: Toward a Theory of Situated AI. ***Academy of Management Review***, 49(3): 618-635.
Kolb, A. Y., & Kolb, D. A. 2005. Learning Styles and Learning Spaces: Enhancing Experiential Learning in Higher Education. ***Academy of Management Learning & Education***, 4(2): 193-212.
Kolb, A. Y., & Kolb, D. A. 2009. Experiential Learning Theory: A Dynamic, Holistic Approach to Management Learning, Education and Development. In S. Armstrong, & C. Fukami (Eds.), ***The SAGE handbook of management learning, education and development***: 42-68. Los Angeles: Sage.
Kolb, D. A. 1984. ***Experiential learning: Experience as the source of learning and development***. Englewood Cliffs, NJ: Prentice Hall.
Larson, B. Z., Moser, C., Caza, A., Muehlfeld, K., & Colombo, L. A. 2024. Critical Thinking in the Age of Generative AI. ***Academy of Management Learning & Education***, 23(3): 1-6.
Lee, H.-p., Sarkar, A., L., T., Drosos, I., Rintel, S., Banks, R., & Wilson, N. 2025. ***The Impact of Generative AI on Critical Thinking: Self-Reported Reductions in Cognitive Effort and Confidence Effects From a Survey of Knowledge Workers***. Paper presented at the CHI Conference on Human Factors in Computing Systems, Yokohama, Japan.
León-Domínguez, U. 2024. Potential cognitive risks of generative transformer-based AI chatbots on higher order executive functions. ***Neuropsychology***.
Lerner, J. S., & Tetlock, P. E. 1999. Accounting for the effects of accountability. ***Psychological Bulletin***, 125(2): 255–275.
Levine, D. P. 2002. Thinking about doing: On learning from experience and the flight from thinking. ***Human Relations***, 55(10): 1251-1268.
Lindebaum, D. 2024. Management learning and education as 'big picture' social science. ***Academy of Management Learning & Education***, 23(1): 1-7.
Lindebaum, D., & Fleming, P. 2024. ChatGPT undermines human reflexivity, scientific responsibility and responsible management research. ***British Journal of Management***, 35(2): 566-575.
Lindebaum, D., Nolan, E., Ashraf, M., Islam, G., & Ramirez, M. F. 2025. The transformation of epistemic agency and governance in higher education through Large Language Models – toward a future of organized immaturity. ***Organization Studies***.
Lindebaum, D., & Ramirez, M. F. 2024. "Negative" resource review: On the essay-writing algorithm Essay Genius at https://essaygenius.ai. ***Academy of Management Learning & Education***, 23(2): 343–345.
Liu, Y., Wu, S., Ruan, M., Chen, S., & Xie, X. Y. 2025. Gen AI Makes People More Productive—and Less Motivated. ***Harvard Business Review***, 13th of May.
Lyons, J. B., Clark, M. A., Wagner, A. R., & Schuelke, M. J. 2017. Certifiable Trust in Autonomous Systems: Making the Intractable Tangible. ***AI Magazine***, 38(3): 37-49.
Martinez, M. E. 2006. What is Metacognition? ***Phi Delta Kappan***, 87(9): 696-699.

Maruping, L. M., Venkatesh, V., Thatcher, S. M. B., & Patel, P. C. 2015. Folding Under Pressure or Rising to the Occasion? Perceived Time Pressure and the Moderating Role of Team Temporal Leadership. ***Academy of Management Journal***, 58(5): 1313-1333.
Miller, T. 2019. Explanation in artificial intelligence: insights from the social sciences. ***Artificial Intelligence***, 267: 1-38.
Mittelstadt, B., Russell, C., & Wachter, S. 2019. Explaining Explanations in AI, ***Proceedings of the Conference on Fairness, Accountability, and Transparency***: 279–288. Atlanta, GA, USA: Association for Computing Machinery.
Moberg, D. J. 2007. Practical Wisdom and Business Ethics: Presidential Address to the Society for Business Ethics Atlanta, August 2006. ***Business Ethics Quarterly***, 17(3): 535-561.
Moser, C., den Hond, F., & Lindebaum, D. 2022. Morality in the age of artificially intelligent algorithms. ***Academy of Management Learning & Education***, 21(1): 139–155.
Moser, C., Glaser, V. L., & Lindebaum, D. 2023. Taking situatedness seriously in theorizing about competitive advantage through AI– a response to "competitive advantages through artificial intelligence: toward a theory of situated AI. ***Academy of Management Review***.
Murray, A., Rhymer, J., & Sirmon, D. G. 2021. Humans and Technology: Forms of Conjoined Agency in Organizations. ***Academy of Management Review***, 46(3): 552-571.
Nair, S., Gaim, M., & Dimov, D. 2022. Toward the Emergence of Entrepreneurial Opportunities: Organizing Early-Phase New Venture Creation Support Systems. ***Academy of Management Review***, 47(1): 162-183.
Nussbaum, M. C. 2001. ***The fragility of goodness: Luck and ethics in Greek tragedy and philosophy***. Cambridge: Cambridge University Press.
O'Sullivan, M. 2017. ***A Macat Analysis of Immanuel Kant's Critique of Pure Reason***. London: Macat International (Routledge Distributor).
Onder, M., & Uzun, M. M. 2021. Roles of Artificial Intelligence (AI) on COVID-19 Pandemic Crisis Management Policies. ***International Journal of Public Administration in the Digital Age***, 8(2): 1-13.
Osterman, P., Kochan, T. A., Locke, R., & Piore, M. J. 2001. ***Working in America: A blueprint for the new labor market***. Cambridge: MIT Press.
Parker, S. K. 2014. Beyond Motivation: Job and Work Design for Development, Health, Ambidexterity, and More. ***Annual Review of Psychology***, 65(Volume 65, 2014): 661-691.
Parker, S. K., & Grote, G. 2022. Automation, Algorithms, and Beyond: Why Work Design Matters More Than Ever in a Digital World. ***Applied Psychology***, 71(4): 1171-1204.
Parker, S. K., Trezise, M., & Thomas, C. S. 2025. Healthier Work in the Age of AI: An Application of the SMART Work Design Model. In A. van Niekerk, N. Harry, & M. Coetzee (Eds.), ***Unlocking Sustainable Wellbeing in the Digital Age: New Avenues for Research and Practice***: 15-31. Cham: Springer Nature Switzerland.
Penn, R., & Scattergood, H. 1985. Deskilling or Enskilling?: An Empirical Investigation of Recent Theories of the Labour Process. ***The British Journal of Sociology***, 36(4): 611-630.
Perlow, L. A. 1999. The Time Famine: Toward a Sociology of Work Time. ***Administrative Science Quarterly***, 44(1): 57-81.
Peters, T., & Austin, N. 1985. MBWA (Managing by Walking Around). ***California Management Review***, 1(Fall): 9-34.
Polanyi, M. 1966. The logic of tacit inference. ***Philosophy***, 41(155): 1-18.
Power, M. 1997. ***The audit society: rituals of verification***. Oxford, UK: Oxford University Press.
Quinn, J. B., Anderson, P., & Finkelstein, S. 1996. Managing professional intellect: making the most of the best. ***Harvard Business Review***, March-April: 71-80.

Raisch, S., & Fomina, K. 2025. Hybrid Problem-Solving with Large Language Models: A Reply to "Iterative Alternative Evaluation" and "An Assemblage Perspective". ***Academy of Management Review***, 50(2): 482-484.

Ramsoomair, N. 2025. Pressing Matters: How AI Irons Out Epistemic Friction and Smooths Over Diversity. ***Atlantis***, 46(1): 42-55.

Ranganathan, A., & Ye, X. M. 2026. AI and machine learning AI Doesn't Reduce Work—It Intensifies It. ***Harvard Business Review***, Retrieved from https://hbr.org/2026/02/ai-doesnt-reduce-work-it-intensifies-it on 2 March 2026.

Regan, P. 2012. Hans-Georg Gadamer's philosophical hermeneutics: Concepts of reading, understanding and interpretation. ***Meta: Research in Hermeneutics, Phenomenology, and Practical Philosophy***, IV(2): 286-303.

Rindermann, H. 2018. ***Cognitive Capitalism: Human Capital and the Wellbeing of Nations (E-book)***. Cambridge, UK: Cambridge University Press.

Roskes, M. 2015. Constraints that Help or Hinder Creative Performance: A Motivational Approach. ***Creativity and Innovation Management***, 24(2): 197-206.

Rousseau, D. M. 2020. The Realist Rationality of Evidence-Based Management. ***Academy of Management Learning & Education***, 19(3): 415-424.

Sarkar, A. 2024. Large Language Models Cannot Explain Themselves. ***ACM CHI 2024 Workshop on Human-Centered Explainable AI***, Retrieved from https://www.microsoft.com/en-us/research/publication/large-language-models-cannot-explain-themselves/ on 28 may 2024.

Sele, K., & Grand, S. 2016. Unpacking the dynamics of ecologies of routines: Mediators and their generative effects in routine interactions. ***Organization Science***, 27(3): 722-738.

Serrat, O. 2017. The Five Whys Technique, ***Knowledge Solutions: Tools, Methods, and Approaches to Drive Organizational Performance***: 307-310. Singapore: Springer Singapore.

Shalvi, S., Eldar, O., & Bereby-Meyer, Y. 2012. Honesty requires time (and lack of justifications). ***Psychological Science***, 23(10): 1264-1270.

Shojaee, P., Mirzadeh, I., Alizadeh, K., Horton, M., Bengio, S., & Farajtabar, M. 2025. The Illusion of Thinking: Understanding the Strengths and Limitations of Reasoning Models via the Lens of Problem Complexity. ***Retrieved from https://ml-site.cdn-apple.com/papers/the-illusion-of-thinking.pdf on 10 June 2025***.

Shotter, J. 2011. ***Getting It: Withness-Thinking and the Dialogical in Practice***. New York: Hampton Press.

Shotter, J., & Tsoukas, H. 2014. In Search of Phronesis: Leadership and the Art of Judgment. ***Academy of Management Learning & Education***, 13(2): 224-243.

Smith, B. C. 2019. ***The Promise of Artificial Intelligence - Reckoning and Judgment***. Cambridge, MA: MIT Press.

Stackpole, T. 2026. LLMs Are Manipulating Users with Rhetorical Tricks. ***Harvard Business Review***, Retrieved from https://hbr.org/2026/03/llms-are-manipulating-users-with-rhetorical-tricks on the 25th of February 2026.

Stadler, M., Bannert, M., & Sailer, M. 2024. Cognitive ease at a cost: LLMs reduce mental effort but compromise depth in student scientific inquiry. ***Computers in Human Behavior***, 160: 108386.

Stichter, M. 2018. Virtue as a skill. In E. Snow, Nancy (Ed.), ***The Oxford Hndbook of Virtue***: 57-80. Oxford: Oxford University Press.

Suddaby, R. 2014. Editor's Comments: Why Theory? ***Academy of Management Review***, 39(4): 407-411.

Tsai, C.-h. 2020. Phronesis and techne: the skill model of wisdom defended. ***Australasian Journal of Philosophy***, 98(2): 234-247.

Tsoukas, H., Hadjimichael, D., Nair, A. K., Pyrko, I., & Wooley, S. 2024. Judgment in business and management research: shedding new light on a familiar concept. ***Academy of Management Annals***, 18(2): 626–669.
Vallor, S. 2024. The Danger Of Superhuman AI Is Not What You Think. ***Noema Magazin***, Retrieved from https://www.noemamag.com/the-danger-of-superhuman-ai-is-not-what-you-think/ on 30 September 2024.
Vered, M., Livni, T., Howe, P. D. L., Miller, T., & Sonenberg, L. 2023. The effects of explanations on automation bias. ***Artificial Intelligence***, 322: 103952.
Yang, Q., Banovic, N., & Zimmerman, J. 2018. Mapping Machine Learning Advances from HCI Research to Reveal Starting Places for Design Innovation, ***Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems***: Paper 130. Montreal QC, Canada: Association for Computing Machinery.
Yu, H., Gan, A., Zhang, K., Tong, S., Liu, Q., & Liu, Z. 2025. ***Evaluation of Retrieval-Augmented Generation: A Survey***, Singapore.
Zajonc, R. B. 1980. Feeling and thinking: Preferences need no inferences. ***American Psychologist***, 35(2): 151-175.
Zao-Sanders, M. 2024. How people are really using GenAI. ***Harvard Business Review***.
Zimmer, M. P., Vassilakopoulou, P., Grisot, M., & Niemimaa, M. 2024. Call for papers: Embracing contrarian thinking: Value-reflexive research for a digital world. ***European Journal of Information Systems***.

FIGURES

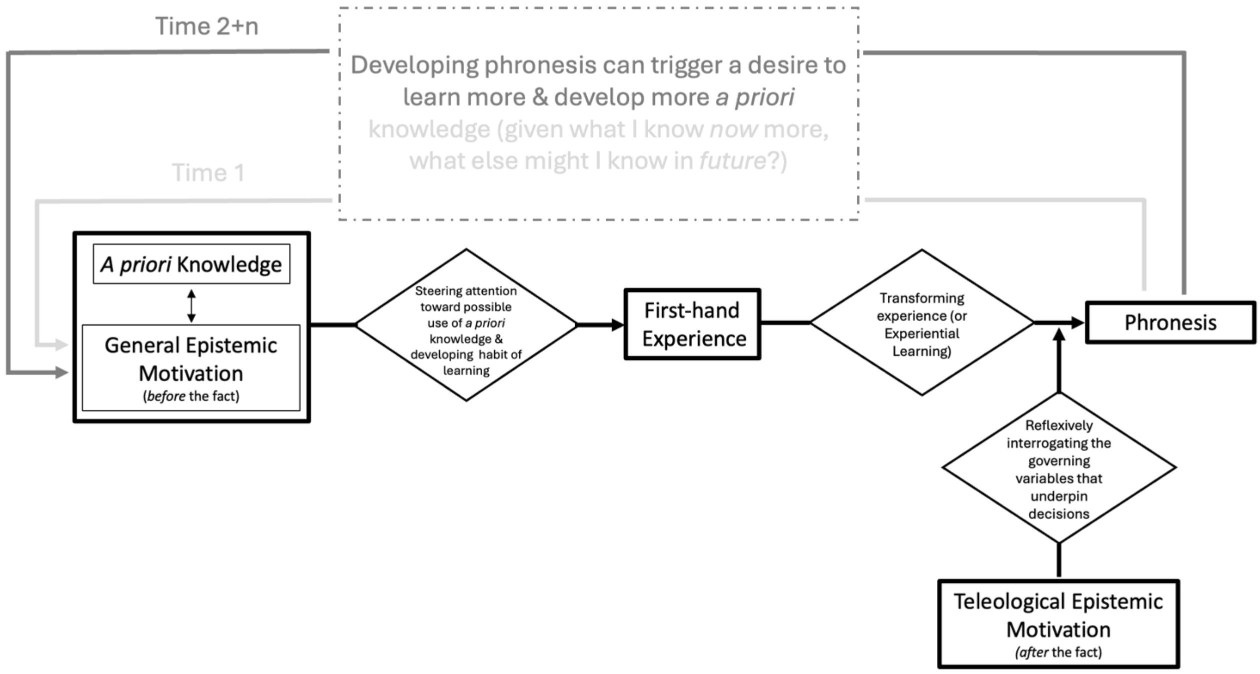

Figure 1: The baseline process model of developing phronesis. Note: Time 1 and Time 2+n indicate that the feedback loop runs over multiple iterations.

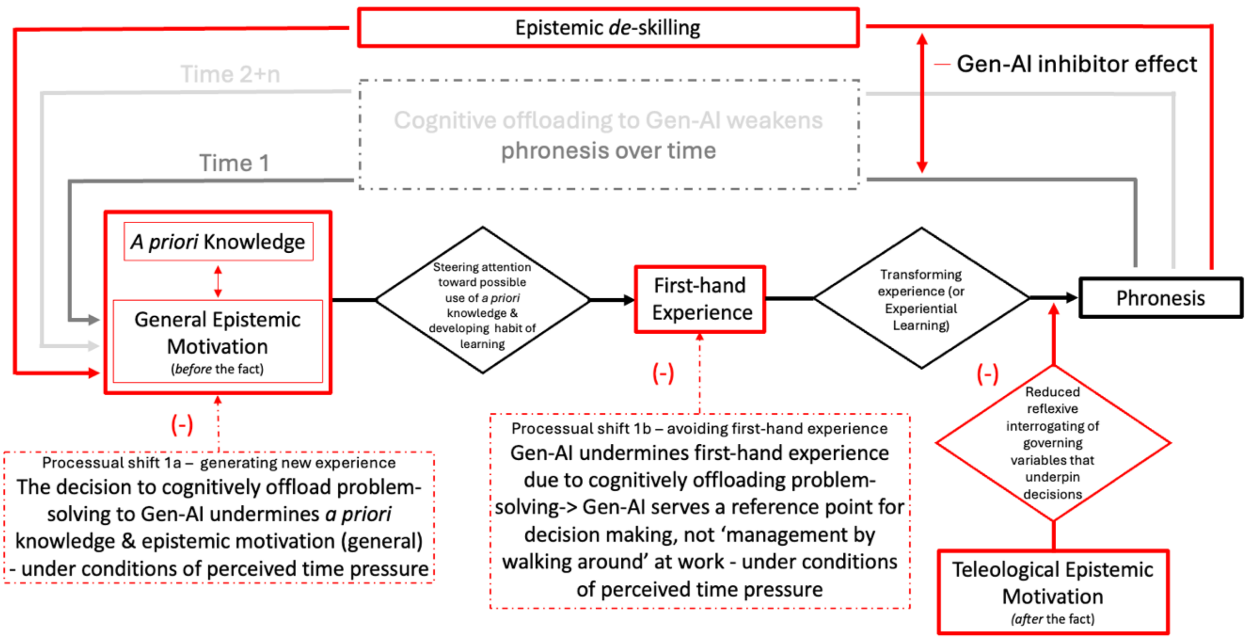

Figure 2a: How Gen-AI affects the baseline process model of developing phronesis through epistemic *de*-skilling (under conditions of perceived time pressure). Note: Time 1 and Time 2+n indicate that the feedback loop runs over multiple iterations.

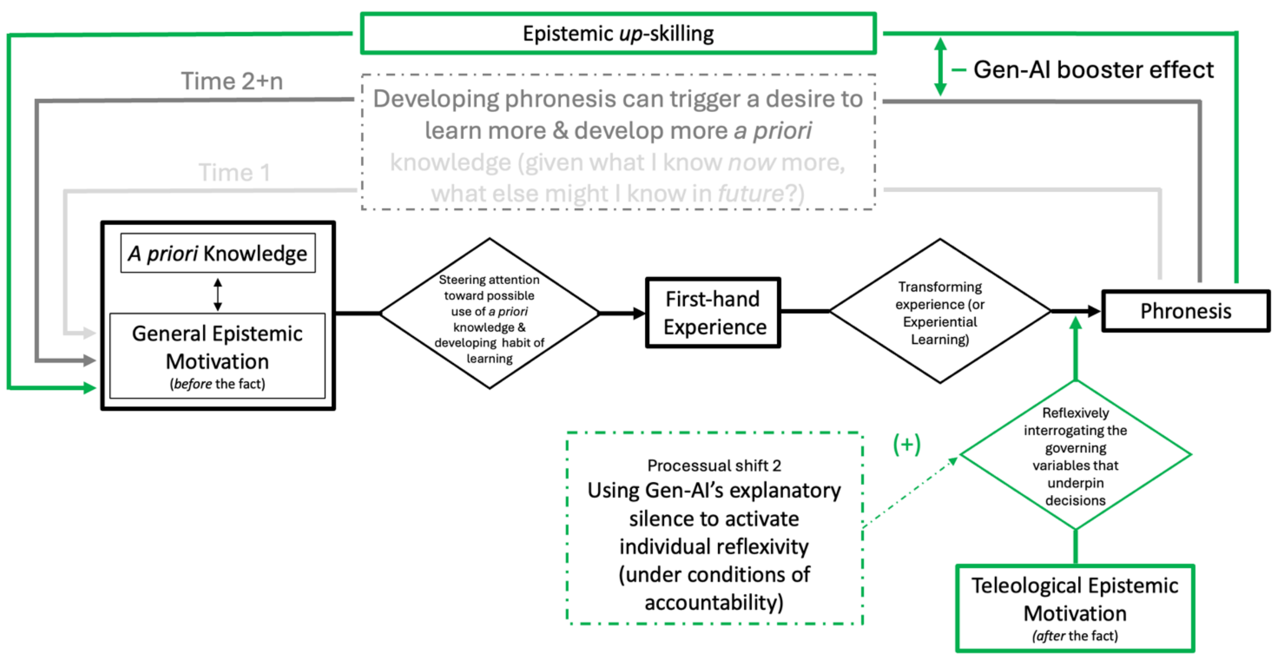

Figure 2b: How Gen-AI affects the baseline process model of developing phronesis through epistemic *up*-skilling (under conditions of accountability). Note: Time 1 and Time 2+n indicate that the feedback loop runs over multiple iterations.

Table 1: Development of the Three Components of Managerial Phronesis in the Presence and Absence of Gen-AI

Components	**How it arises in baseline model**	**How Gen-AI may affect components (via epistemic de and up-skilling)**	
		Epistemic de-skilling	*Epistemic up-skilling*
Moral Insights	From first-hand experience involving social interactions, where motivated learners seek to activate a priori knowledge to deal with morally puzzling situations.	Processual Shift 1a: Prospective emotional disengagement and impoverished a priori knowledge weaken possible moral insights through reduced questioning. Processual Shift 1b: Lack of first-hand experience of actions and outcomes limits normative deliberation; Gen-AI effectively reproduce the most probable responses based on its training data.	Processual Shift 2: Generate hypothetical scenarios for learners to deliberate and enhance ethical interrogation in a limited way (much like Gen-AI can only help in a limited way to be a better wine taster)
Contextual Sensitivity	From first-hand experience in the focal contexts that helps motivated learners to activate a priori knowledge to identify and understand relevant context through reflexive interrogation; second-hand learning of some context-specific "rules" possible.	Processual Shift 1a: Increased passivity to develop contextual sensitivity proactively (i.e., diminished motivation to explore future possibilities). Processual Shift 1b: Gen-AI offers generalized framings in response to existing problems, which implies reduced contextual sensitivity	Processual Shift 2: Hypothetical context generation can be used to test and enhance contextual sensitivity by contrasting simulated contexts with focal context.
Practical Know-how	From first-hand experience involving repeated application and practice of skill and knowledge by motivated learners through reflexive interrogation; second-hand learning of some foundational principles possible.	Processual Shift 1a) Increased passivity lessens practical know-how by reducing motivation to explore. Processual Shift 1b: Gen-AI performs tasks on learner's behalf and directly reduces practice & application of skill or knowledge.	Processual Shift 2: Gen-AI augments reflexive experimentation, scenario testing and post-hoc evaluation while leaving situated enactment to the manager.