Knowledge Sufficiency in the Era of Contemporary Digital Technologies

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Abstract: Knowledge management (KM) and the related literature on intellectual capital (IC) have a long-standing tradition of emphasizing the fundamental role of human knowledge, including know-how, reasoning, and judgement, as the central pillar of organizational decision-making and value creation. It represents one of the key aspects of what has been traditionally considered as "sufficient" knowledge utilized in knowledge work and to successfully conducting complex knowledge-intensive work tasks. In this school of thought, humans are seen as reliable agents while non-human sources, such as digital technologies, pose technical and institutional risks. Simultaneously, a corpus of scholarly work in management and information systems has argued and provided empirical evidence on the superiority of digital technology enabled data-driven decisions in terms of their quickness and accuracy, claiming that algorithms consistently outperform humans in decision-making. In this school of thought, the cognitive limitations of human agents and the risk of potential occurrence of human error are underlined, while the processing power and consistency of digital technologies considered a gold standard. To overcome the hurdle related to "algorithmic aversion" yet mitigating the risk of falling to the trap of "artificial certainty", this study embarks 1) conceptualizing knowledge sufficiency in the era of contemporary digital technologies and 2) elaborating the degree of technological assistance required to reach the elusive levels of knowledge sufficiency in complex, non-routine organizational tasks and processes. Through conceptual work and empirical snippets, this study helps organizations maximize the benefits of technology-driven knowledge while safeguarding the uncertainties of critical decisions, helping them to successfully navigate the landscape of contemporary digital technologies.

Keywords: Knowledge management, Knowledge sufficiency, Algorithmic aversion, Artificial certainty

1. Introduction

Technological progress is inevitable. Technological innovations emerge at a tremendously fast pace and some of the novel digital technologies have already had major impact on individuals, organizations, and societies – especially knowledge work, wherein these new tools are shaped by and shape daily work practices (Chen et al, 2025; Sowa et al, 2021; van den Broek, 2025). Yet, organizations struggle to keep up with the pace of change because instead of progressing – like technology does – institutions and organizations tend to merely change (Berente and Seidel, 2022; Bush, 1987; Van de Ven and Hargrave, 2004). Therefore, constantly evolving digital technologies, such as different types as artificial intelligence, and the cyclical nature of organizational change may clash at times, causing misalignment, e.g., related to the novel opportunities enabled by digital technologies and how effectively organizations manage to seize the opportunities. This emerging phenomenon opens avenues for academics and practitioners to elaborate on the approaches and solutions that could provide better alignment and understanding that would allow knowledge workers and decision-makers to benefit from technological progress amid recurring organizational change.

Knowledge management (KM) and intellectual capital (IC) scholarships traditionally perceive human-bound knowledge as the de facto basis of organizational wealth and value creation (Edvinsson and Sullivan, 1996; Sveiby, 1997). Human knowledge has been shown to be the central precondition of innovation and therefore firm competitiveness (Eriksson et al., 2023; Inkinen, 2015), making it a strategic resource for firm survival and performance (Sveiby, 2001). In this paradigm, human creativity, know-how and reasoning are impossible to replace with digital technologies that are primarily designed to predict, classify or optimize (e.g. Hacker et al, 2023). Moreover, these technological, non-human sources of insight and knowledge are perceived to pose technical and institutional risks, both potential causes for error and unwanted adverse consequences. For instance, literature identifies data vulnerabilities, safety and robustness issues (e.g. AI hallucination), algorithmic bias, data privacy and ethical breaches, and lack (or loss) of control as technical risks connected to the use of data and digital technologies in organizations (Berente and Seidel, 2022; Brewer et al, 2024; Ciborra, 2006; Kessler et al, 2022; Mikalef et al., 2025). Furthermore, organizational risks including overreliance, accountability, governance, compliance, reputational, and operational issues are discussed as potential unwanted outcomes related to the use of data and digital technologies – especially AI (Berente et al, 2021; Boone et al, 2025; Sharma et al, 2024; Zhao and Wang, 2024). From the knowledge-based perspective, these risks are pronounced, as they may affect organizational knowledge processes and routines, including knowledge creation, sharing, dissemination, reuse and retention, potentially leading knowledge loss, unintentional knowledge leakage, lower knowledge quality or reputational consequences (Böhm and Durst, 2026; Durst and Zieba, 2019; Yan et al, 2026).

Despite of the known risks and the looming uncertainties, another corpus of literature strongly emphasizes the benefits of technology-enabled (i.e. data-driven) decision-making in organizations in terms of its quickness and accuracy (e.g. Brynjolfsson et al, 2021; Cao and Duan, 2024; Lepenioti et al., 2020), leading scholars to argue that algorithms consistently outperform humans in decision-making (e.g. Dietvorst et al, 2015; Mudassir et al, 2024). That said, recent information systems literature suggest that the use of digital technologies can be categorized into automation and augmentation, depending on what purposes it is deployed: In automation, these technologies are used to replace humans mostly in repetitive and highly structured tasks, while in augmentation digital technology is used to assist humans performing more complex and non-routine tasks (Enholm et al, 2021). In the case of automation humans are decreasingly or not at all involved in the automated tasks or processes, making their stance towards digital technologies almost irrelevant (out of sight – out of mind). However, in the augmentative use of digital technologies, humans retain a central position in tasks and processes wherein these technologies are introduced, making their willingness to accept new digital technologies critical. Therefore, it is feasible to focus exclusively on augmentative use of digital technologies in this study.

While the human-bound and pro-technology schools of thought have seemingly solid arguments with heaps of empirical backing, this study proposes that sufficient knowledge in the era of digital technologies does not sprout from either extreme but rather from a combination of lowered expectations towards algorithms and safeguarding the essential role of uncertainty while conducting complex tasks and making impactful decisions. To do this, we must first define knowledge sufficiency and how it should be perceived in the era of digital technologies. After that we must elaborate the root causes and potential remedy for "algorithmic aversion", defined as "the tendency of individuals to resist or reject algorithmic recommendations in favor of human judgment" (Ling and Yan, 2026). Finally, we must discuss the dangers of "artificial certainty", i.e., the illusion that complex future outcomes are fully knowable, potentially leading the users of digitally crafted knowledge mistake e.g. simulations for reality (Leonardi and Leavell, 2026). Combining these three, this study pinpoints the disadvantages of algorithmic aversion in complex knowledge work and various decision-making contexts wherein artificial certainty yields high chances of failure and only little value. The gained new level of clarity would allow more effective and responsible utilization of digital technology-enabled opportunities in organizations of all types and sizes.

2. Conceptual Background

2.1 Knowledge Sufficiency

The concept of sufficiency has gained contemporary prevalence especially in the realm of ecological economics. The premise is "that reaching a state of 'enough' is desirable both from the perspective of ecosystems, as well as from the point of view of social and economic systems" (Jungell-Michelsson and Heikkurinen, 2022). Or, as Figge et al (2014, p.217) crystallize, sufficiency stands for "living well on less". From a more philosophical standpoint, knowledge sufficiency is defined as "the right sort of match between one's justification and the facts, where that match involves the justification somehow being 'good enough' to 'stand up to' the facts" (Schroeder, 2015, p. 236). This justification happens through reasoning – both objective and subjective – which establishes the sufficiency and weight of these reasons (Schroeder, 2015). Previous management literature has also addressed knowledge sufficiency, but this account is limited to very specific contextual conditions. For instance, Hopkins (2014) explored knowledge sufficiency through the breadth, depth, and quality of knowledge firms gather from potential host countries prior to market entry, noticing that strategic decision-makers may feel overconfident about the depth of their knowledge, leading to suboptimal selection of host country and the mode of entry.

From the knowledge-based perspective, knowledge sufficiency can be defined as *the degree of knowledge that is good enough to justify the decisions that help an organization reach its operational and strategic targets*. At the core of this definition is the right sort of balance and match between the task at hand, characterized by the complexity of a given task or decision, and the (minimum) level of knowledge and the related certainty that allows organizations or decision-makers to justify and commit to the decision. Applying this principle to the use of contemporary digital technologies requires organizations to re-assess how do they perceive and treat technologies as sources (or producers) of knowledge and insight as well as mechanisms (or consumers) through which complex tasks are conducted in organizations. Kogut and Zander (1992) stress that organizations are ought to understand "what they know how to do", which leads to better organizing and effective seizing of technological opportunities. This suggests that the mere acquiring and use of technology does not lead to seizing opportunities, but it is rather the organizational understanding of the underlying knowledge-related needs that should be driving technology adoption and utilization (Gupta and George, 2016; Mikalef and Gupta, 2021). Business Area Director of a large Finnish forestry company crystalized the concept of knowledge sufficiency in practice when enquired about the expectations on the coverage and accuracy of insight gained through their production optimization system:

> *"Sufficiency of data-driven insight in decision-making depends on the level of accuracy required in each context and decision. When the tolerances are high, it is better not to seek a perfect answer to a question, but rather a "thumbs up or thumbs down" type of answer that gives additional assurance on the decisions we are making and speeds up the decision-making process."*

Another interviewee – a Business Division Director of a Finnish energy company – had similar views:

> *"We should use data for decision-making when the possibilities for variance of outcomes are very small. When the outcome is very open and wide and relates to, for instance, people's or consumers' preferences, the role of data diminishes."*

Head of Project Controlling of a Finnish energy company shared us a more detailed example:

> *"You know, sometimes the weeks and months are action-packed, very busy, and consequently you as a leader do not have as much time as you would like to check up on your people. Experience of course helps to establish quite a reliable gut feeling on how they are doing and feeling, but I always double-check the facts from the monthly work wellbeing survey results. This, combined with my professional experience, is all I need to go forward with confidence."*

This implies that in augmentative use of digital technologies, very often characterized by high tolerances and uncertain contexts of use, such as non-routine strategic decisions, lowered expectations for digital technologies and algorithms may become beneficial, as they are usually utilized in tandem with a plethora of other information and knowledge sources, yet producing valuable confirmatory evidence for decision-makers (e.g. Orjatsalo et al, 2025). However, many organizations and decision-makers still struggle to correct their courses in terms of trusting the technology-driven knowledge, leading them to exhibit algorithmic aversion – a concept that we elaborate next.

2.2 Algorithmic Aversion

One of the major obstacles to digital technology adoption and use in organizations is algorithmic aversion – "The phenomenon in which people often obey inferior human decisions, even if they understand that algorithmic decisions outperform them" (Dietvorst et al, 2015). Algorithmic aversion and acceptance have their roots more often in the subjective human bias and prejudice instead of objective true performance of digital technologies (de Jong et al, 2025). Therefore, making informational management interventions on data end technology use is quite ineffective in organizations (Kaiser et al, 2025). However, humans and algorithms may achieve surprisingly similar results when asked to perform the same task (Rajaram and Tinguely, 2024), making this bias rather alarming. In addition, people may become highly reluctant to use digital technologies after seeing them make mistakes but forgive human errors more easily (de John et al, 2025), causing asymmetrical forgiveness and decision-makers preferring people over algorithms (Dietvorst et al, 2015). A Chief Technology Officer of a Finnish OEM company talked about this phenomenon as follows:

> *"Our company and employees are technology tolerant and see digital innovations as opportunities to accomplish our targets and tasks faster and more accurately. However, it still surprises us how a digital technology that we have used for quite a long time, and which has become a key part of our daily routines, gets distrusted and even despised when it makes a rare mistake. Maybe it shows how recent these technological introductions are in a bigger picture and how little experience we have on handling these odd situations as an organization and individuals."*

This behavior is in our DNA though, as human-bound expertise has a long-standing tradition of being trusted as the primary or even the only source of relevant and reliable insight, as emphasized in the extensive corpus of KM and IC literature (Edvinsson and Sullivan, 1996; Grant, 1996; Spender, 1996; Sveiby, 1997). It manifests from recurring, routine-like decisions to complex strategic decisions, often emphasizing the tenure and more integrated position of an individual (Schulzmann and Martins, 2018), while the insights generated through data and algorithms are often required to be validated by human decision-makers (Kumar et al, 2024). As underlined in the previous section, this setup does not have to drastically change in augmentative use of digital technologies, as the human actor will continue to be a central figure and responsible for making the decisions. However, adjustments such as gradually increasing the prevalence of data and algorithms in solving complex problems is a mandatory step to be taken in many organizations, as ramping up the use of data and digital technologies as new data sources – in combination with the existing organizational knowledge – generally leads to better decisions (Brown, 2021; Stobierski, 2019). In other words, choosing not to use new digital technologies may severely limit an organization's competitiveness (Ruokonen and Ritala, 2025).

From a different viewpoint, algorithmic aversion might be a trait of an organization that acts according to high ethical standards, demonstrating risk-aversive or risk-conscious behavior to secure a more sustainable future by avoiding establishing artificial certainty into their crucial decision-making processes.

2.3 Artificial Certainty

The extant information systems research has produced strong arguments regarding the clear benefits of data-driven approaches in replacing humans in task and process automation (Dietvorst et al, 2015; Enholm et al, 2021; Mudassir et al, 2024). However, much less attention is given to areas where algorithms are considerably less useful (e.g., complex, non-routine decisions) and even a root cause of artificial certainty and the related adverse effects. Artificial certainty, defined as "the production of representations that appear authoritative, concrete, and unambiguous despite depicting inherently uncertain phenomena" (Leonardi and Leavell, 2026), could be especially damaging for organizations in situations that are characterized by elevated risks and high levels of uncertainty, as it may bear long-term consequences on the focal organization.

Intelligence, as traditionally perceived by humans, represents critical thinking, continuous learning and application of the accumulated knowledge, creativity, know-how and know-why, with nearly all these traits out of reach of digital technologies and even the most cutting-edge artificial intelligence solutions, even though their developers have tried their best to mimic and embed human intelligence and cognition into these tools (Jaeger, 2023; Jarrahi et al, 2023). Therefore, from the knowledge-based perspective, we can argue that there is no artificial intelligence. Instead, prior research has shown how experts using advanced digital technologies can create artificial certainty, i.e., the illusion that complex future outcomes are fully knowable (Leonardi and Leavell, 2026). In the age of digital technologies, preserving real uncertainties becomes a critical management skill that requires deep contextual understanding and reasoning, helping decision-makers establish whether the digitally crafted knowledge is sufficient and close enough to the facts and realities (Schroeder, 2015) – or otherwise, there is a risk that artificial certainty gets institutionalized through organization's information systems (Leonardi and Leavell, 2026). Business Development Director of a Finnish manufacturing company said the following:

> *"It depends on the user of a smartphone how smart the phone really turns out. If you believe everything you see and read, you are going to get it wrong at some point. The same applies to our data sources and information systems that should be accompanied by in depth understanding and a healthy degree of critical thinking. I believe that if data 'reveals' you something completely new or something that you would not never think of before, then you should probably go back to the drawing board and learn how to become a better business leader."*

CEO of an energy company contemplated the clash between a human-made company vision and the increased use of data-driven decisions:

> *"[Decision-makers] fight over data instead of fighting over the vision, because vision is difficult. The risk is that when the uncertainty grows, we cut the border conditions from what our vision is, so the analysis gets more handleable for us. But then we cut border condition after another, so the data analysis does no longer describe what we wanted to originally investigate or describe."*

This suggests that artificial certainty is not driven only by the lack of managerial reasoning capability but also influenced by the intentional use of data-driven predictions and analysis to promote the preferred or even predetermined decisions of some organizational actors. In behavioural economics literature, this phenomenon is referred to as confirmation bias, where ideas or recommendations that confirm personal believes are heavily emphasized over credible alternatives that contradict them (Kahneman et al, 2011; Tversky and Kahneman, 1974). From the knowledge-based perspective, such biased approach is deemed undesirable, as the KM activities and practices in an organization should be targeted to creation, development, sharing, organization, and leverage of knowledge that maximizes an organization's chances of reaching elevated levels of performance and results – both strategic and operational (Davenport et al, 1998; Demarest, 1997; Wiig, 1997). Therefore, if the outputs of digital technologies – a critical component of contemporary organization's knowledge base – are utilized for argumentative purposes without a deep understanding of the context of use or to drive a biased agenda, the outcomes are very likely to be underwhelming.

3. Discussion

This study had the objective to explore what constitutes knowledge sufficiency in the era of contemporary digital technologies. This was elaborated particularly from the knowledge workers' and decision-makers' viewpoints, as well as focusing on the augmentative use of these technologies in complex organizational tasks and processes. First, through theoretical work we defined knowledge sufficiency as *the degree of knowledge that is good enough to justify the decisions that help an organization reach its operational and strategic targets.* Then we discussed how contemporary digital technologies, such as artificial intelligence, may help organizations and individuals establish this elusive level of sufficient knowledge. Using empirical passages collected from large Finnish companies on top of our theoretical premises, we propose that two border conditions must be addressed – algorithmic aversion and artificial certainty – as they might cause too restricted or liberal use of these technologies in critical organizational tasks, such as decision making.

First, the paper proposes that knowledge workers and decision-makers could benefit from lowered expectations towards algorithms, as they represent only one of many information sources used to accomplish complex tasks. Therefore, digitally crafted knowledge should not be expected to be perfect or flawless, as neither is human-bound knowledge, nor a replacement of human judgement and reasoning, but as a reliable and factual-based knowledge source that helps decision-makers sleep better at night knowing that they have made the right decisions. Digital technologies carry their risks and weaknesses, but in the augmentative purposes they should be seen as providers of indicative knowledge that helps guide decisions approximately into correct direction, enhancing the speed and robustness of the made decisions.

Second, safeguarding real uncertainties is crucial, as otherwise we may get fooled to think that we can generate answers and explanations through digital technologies to questions or phenomena that are inherently uncertain. Instead, developing understanding about the intelligence-related limitations of these tools and ensuring the presence of human actors in contexts characterized by complexity can help organizations avoid overreliance on algorithms and secure the presence of human actors in tasks where human reasoning is unmatched, such as developing a company vision.

Relatedly, we propose the future research to dive deeper into these issues through three interrelated research avenues. First, knowledge sufficiency should be assessed in organizations operating in various industries and geographical contexts, as cultural traits may act a central role in how digitally crafter knowledge is perceived. Second, algorithmic aversion in augmentative use of artificial intelligence is still in its infancy, allowing research opportunities for scholars to identify the root causes for such behaviour among top-managers working in different industries. Third, even though artificial certainty is labelled as a risky and unwanted situation for organizations, the future research could go beyond the current understanding by showing examples where it could have also positive effects.

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AI Declaration: AI tools were not used in the creation of this paper.

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