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# Knowledge Asymmetry: Are We Destined to Become the Ignorant Lords of Algorithms?

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*Short Paper*

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## *Abstract*

*Artificial Intelligence (AI) is inextricably linked to knowledge and the management of knowledge. This paper highlights the ethical concerns related to the use of algorithms in the context of hybrid intelligence teams and the dimensions of knowledge asymmetry that exist. The research question motivating our paper is: How is knowledge asymmetry characterised in Human-AI Collaboration eliciting ethical concerns? We first present a brief overview of the literature on knowledge asymmetry and knowledge transfer. We then propose four scenarios of knowledge asymmetry in Human-AI Collaboration, based on real-world cases. Finally, we highlight the ethical concerns linked with each of these scenarios.*

**Keywords:** Artificial Intelligence, Knowledge Management, Knowledge Asymmetry, Knowledge, Know-how, Information Asymmetry, Ethics, Hybrid Intelligence Systems, Collaboration.

## Introduction

Artificial Intelligence (AI) is the study of how to make computers perform intelligent tasks, such as learning, judgement, and decision-making, that used to be wholly performed by humans (Legg and Hutter, 2007). Arguably, knowledge management (KM) is considered to be the raw material of AI (Duan and Xu, 2012), building on this definition, there will undoubtedly be knowledge asymmetry, a "concept metaphor" (Moore, 2004; Jacobsen, 2014) that "distinguishes outstanding individuals in a domain from less outstanding individuals in that domain as well as from people in general" (Jacobsen (2014) citing Ericsson, 1991:2). This being the case, leveraging the use of powerful algorithms within an AI system, for instance to increase operational efficiencies, enhance customer experience, and improve strategic planning can also bring real risks. In the context of a modern organisational setting, the use of AI alongside humans with professional knowledge and expertise raises ethical concerns related to the collaboration between Human and AI (H-AI-C). Often referred to as "hybrid intelligent systems", the combination of abilities and types of intelligence enables the achievement of more than would have been possible if every agent performed on its own (Dellermann et al., 2021). In order to address our research question, 'How is knowledge asymmetry characterised in Human-AI Collaboration eliciting ethical concerns?', we first need to understand the relationship between knowledge asymmetry and knowledge transfer in AI and hybrid intelligent systems. Building on this brief review of the literature, we will then present four scenarios of knowledge asymmetry in Human-AI Collaboration, based on real-world cases. Finally, we will highlight the ethical concerns linked with each of these scenarios and make recommendations for future research.

## Advances in AI

AI capabilities and applications are growing rapidly, leading to change in people's lifestyles (Huang, Cai et al., 2019). Historically, one of the first applications of AI was rule-based systems (RBS) (also called expert systems, Addis, 1956), which required explicit decision-making rules to be coded by a knowledge manager based on the knowledge imparted by a subject matter expert (Feuerriegel et al., 2020). The advent of the

World Wide Web and the application of Machine Learning (ML) approaches enabled AI to 'learn' autonomously from data using probabilistic approaches (Kraus et al., 2020), leading to faster and more accurate results in certain contexts. The progress of AI has raised and continues to raise serious ethical concerns, one of which is that selected variables in AI models aren't necessarily deemed relevant or even fair by human common-sense (Miller and Record, 2013; Mittelstadt et al., 2016).

Debates around the influence of algorithms and stronger forms of AI on the human condition are emerging. They question whether AI would enslave humans (Kim et al., 2021). Le Cun (2019) argues that AI is far from planning to become our master unless we explicitly programme it to, stating that contrary to humans, AI today hasn't been naturally selected to engage in power or influence games. In fact, Coeckelbergh (2015) fears that the biggest tragedy is for humans to become the ignorant alienated "super-masters" of AI, only taking charge of managerial and supervision tasks, while leaving AI to perform the activities related to the physical world (Coeckelbergh, 2015). Others argue that over time AI will eventually take control of humans (Alexandre, 2017; Bostrom, 2017).

## Knowledge transmission mechanisms among humans and between humans and AI

Know-how is a fundamental pillar of human civilization (Grant, 1996). In epistemological studies, the concepts of "knowledge-that" (or propositional knowledge), "knowledge-why" (or understanding), "knowledge-how" (or know-how), and the ability to perform a task are differentiated from one another (Miller, 2020; Grimm, 2019; Sullivan, 2018; De Brigard, 2019). Each type of knowledge has its characteristics (Grimm, 2019). Ongoing debates point to the difficulty of transmitting knowledge depending on its type and other conjunctural factors (Carter and Poston, 2018; Grimm, 2019). The process of sharing knowledge (i.e., transmitting and reusing knowledge) reveals itself to be complex among humans, especially as we move from propositional knowledge to understanding and know-how since these two types are "[instances] of some-work-required transmission" on the part of the receiver (Grimm, 2019:126).

The advent of Information Systems and AI has introduced new users and producers of knowledge: algorithms and machines. Considering knowledge transmission between humans and AI, we believe there is a two-way street. First, humans must transmit part of their knowledge to AI for it to provide further analysis and results. This transmission takes the form of providing different examples to AI algorithms to learn from (i.e., Transfer Learning (Cai et al., 2020) and Learning from Demonstration (Rivas-Blanco et al., 2019)). However, when we study knowledge transmission from AI to humans, AI monopolisation of knowledge emerges as a cardinal issue (Coeckelbergh, 2015). Some of its knowledge artefacts (e.g., rules, decisions, and actions) are not understandable by humans and even referred to as the "black box problem" (Castelvecchi, 2016). In this context, we can also refer to Wittgenstein's (2010: 223) idea: "if a lion would speak, we could not understand him". In other words, even if AI algorithms build their rules and conclusions from human-provided data and demonstrations, they still do not share the same lived experience of humans, and consequently cannot easily share human judgement and understanding nor the same working processes, as illustrated by Anichini and Geffroy (2021).

## Knowledge asymmetry in Human-AI teams

Knowledge and Information are two concepts that generate some confusion in the literature (Li, 2021; Godbout, 1998). While acknowledging the difficulty in distinguishing both concepts, many authors have attempted to suggest definitions in ways that would distinguish them (Singh, 2007). For instance, information has been defined as "organized data" (Saint-Onge, 2002), "data endowed with relevance and purpose" (Drucker, 2012), and "the data that has been processed into a form that is meaningful to the recipient" (Daniel, 1984); and knowledge has been defined as "a true and justified belief" (Nonaka and Takeuchi, 1995), "acquired by thinking" (Machlup, 1983), "internal [and not something that] cannot be received but must be internally created" (Hayes, 1993), "[residing] in the minds of people; once it is outside the human mind, it is information" (Al-Hawamdeh, 2003).

Considering interactions between several actors, the levels of information and knowledge possessed by each actor vary. This condition where "one party in a relationship has more or better information [or knowledge] than another" (Bergh et al., 2019 citing Ackerloff, 1970) is called information/knowledge asymmetry. While management research literature doesn't clearly discuss the concept of knowledge asymmetry, it uses the terms "knowledge" and "information" interchangeably (e.g., Bergh et al., 2019, Ecker et al., 2013; Hambrick and Mason, 1984), which blurs the difference between the two concepts further.

The mastery of knowledge (in both its tacit and explicit forms) is the keystone element of expertise, and it is the very reason we trust our experts. Social institutions provide credibility to experts. They (lawyers, doctors, engineers, etc.) go through a lengthy training process whereby they are confronted with theoretical and empirical knowledge. We trust and allow them to function as black boxes based on the credibility we assign to their training institutions and mentors. However, in the context of collaboration, where parties are called to "combine their perspectives to search for solutions that extend beyond what one may accomplish in isolation" (Banks et al., 2016: 2208), we observe the emergence of knowledge asymmetries (Banks et al., 2016). Knowledge asymmetry, when viewed as a construct (Bergh et al., 2019), negatively influences collaboration which leads to more isolated knowledge creation and less knowledge co-creation. Moreover, Banks et al. (2016) suggest that effective knowledge transfer requires the presence of optimal communication channels whereby parties can exchange their newly created knowledge.

Regarding AI, the mechanisms of expertise present in human social groups are absent: 1) AI can hardly explain its decision-making process to other experts, 2) it has no trustworthy social institutions to certify its decision-making and no socialisation or direct experience in each context, consequently, the knowledge asymmetry between humans and AI can be perceived as a threat. AI applied to expert knowledge only treats the tip of the iceberg. In human groups, knowledge asymmetry between the holder of knowledge and know-how (practitioner or expert) and the beneficiary of the end-product (observer) is overcome by trust between the parties (Tsoukas, 2004). However, practitioners and experts are expected to interact between themselves and to be transparent when need be. Algorithms currently lack these aspects of explainability and transparency compared with other experts and, consequently, are transposing the knowledge asymmetry issue at the core of the "expert systems" themselves (if we consider that expert systems are a combination of human experts and expert algorithms). Moreover, there is little literature attempting to approach knowledge transfer from algorithms to humans in a way that enables actual collaboration and that invites experts to consider algorithms as teammates as opposed to a suspicious entity. If not controlled and monitored, the path towards deferring our real-world knowledge and know-how to algorithms could follow a slippery slope leading to the more pessimistic endgame of AI.

## Ethical concerns around knowledge asymmetry

Knowledge asymmetry undoubtedly raises ethical concerns. The most apparent according to Coeckelbergh (2015) is loss of autonomy. When an agent has less knowledge than another, they cannot make the best decisions, and if they let another agent amass all their know-how, they lose their ability to exercise their expertise. They become dependent on the agent holding more knowledge and know-how. Moreover, this agent may not hold the same values as them, which may lead to misalignment between their values and the actual consequences of the decisions they make when relying on another agents' recommendations. Moreover, in the context of knowledge asymmetry between humans and AI systems, it is not clear where the responsibility for decisions assisted by machines lays, if it is with the expert who knowingly used the AI, with the AI designers, or with the beneficiaries of the decision who may or may not have used informed consent to agree with the AI-decisions (Neri et al., 2020).

Knowledge transfer between humans and AI can be a way to address knowledge asymmetry between human agents and machine agents, and consequently to mitigate some ethical concerns. Algorithms should be considered as teammates rather than mere tools (Seeber et al., 2020). For instance, in the case of bias in decision-making, algorithms have been shown to reproduce and even amplify human bias (Mittelstadt et al., 2016; Obermeyer et al., 2019; Alikhademi et al., 2021) in ways that point out past human short-sightedness and discriminations towards some social groups and classes. Such instances of bias are a call for humans to be more aware of their own biases and address them accordingly, rather than feeding algorithms with data and becoming a slave to their recommendations. Knowledge asymmetry in Human-AI collaboration is unequivocally two-sided. It favours algorithms in the case of automated processes and tasks where large quantities of data are at play, and favours humans when attributing value to decisions, thinking of ways to correct them, and adapting them in the case of hazardous situations (Nagar and Malone, 2011). In what follows, we will investigate different scenarios of knowledge asymmetry in human-AI collaboration and the related ethical issues.

## Methodology

Based on this literature review, and our review of some AI algorithms (Elsayed Fayed, 2021; Sun et al., 2022; Floridi, 2014), we propose a categorisation for the distribution of knowledge between human agents and AI. This categorisation offers four possibilities where AI gains more knowledge with every scenario. AI gaining and processing knowledge is dependent on the complexity of the models, algorithms, data and algorithms AI feeds on. Here, we present a high-level framework to approach human-AI knowledge asymmetry based on our initial literature review using the key words (Artificial Intelligence, Ethics, Knowledge, Know-How, Knowledge Asymmetry, Information Asymmetry) in the databases Web of Science and Google Scholar. Based on this, we started to set up criteria that would help differentiate scenarios with distinct knowledge asymmetry in human-AI collaboration. The examples emerged from the search for cases that fulfilled the à priori criteria we set for every scenarios. The following section presents our early findings, Future research will extend the depth and breadth of the literature review and develop these models further.

## Scenarios and typology of collaborative modes

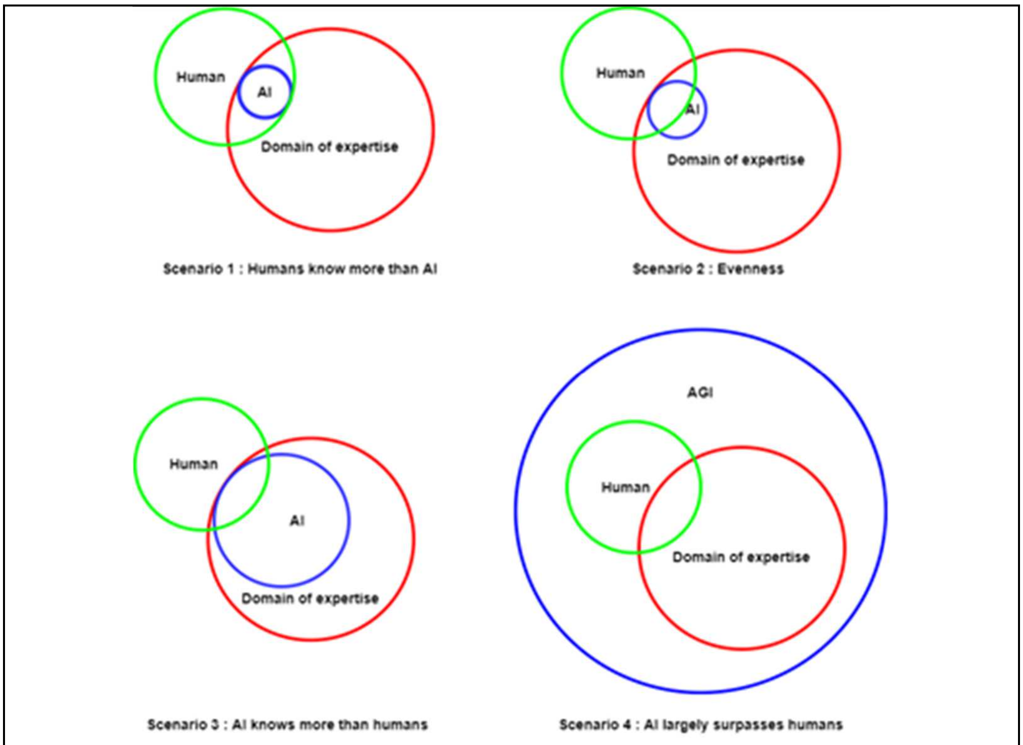


**Figure 1. Scenarios of knowledge asymmetry in Human-AI Collaboration.**

Since our main focus is knowledge asymmetry in Human-AI relationships, we suggest four main scenarios of knowledge asymmetry (Figure 1) : 1) The scope of what humans know in a given domain of expertise is superior to that of AI, 2) The scope of what humans know is equivalent to that of AI, 3) The scope of what AI knows is superior to that of humans, yet humans master some aspects that are foreign to AI, and 4) The scope of what AI knows is largely superior to that of humans. In figure (1) circles represent knowledge:

1) The green circles represent human knowledge necessary to perform in a given field. This knowledge is a combination of propositional knowledge, understanding, knowledge-how, and abilities to perform tasks given these elements of knowledge. Human knowledge goes beyond knowledge specific to a field since humans can adapt to new situations when they rely on other more general forms of knowledge.

2) The red circles represent knowledge in a given field. It goes beyond what humans may already know for two main reasons: i) the human team may not have all experts in that field, consequently they cannot cover all the field of expertise on their own, and ii) knowledge is an open quest, there are always more elements of knowledge to uncover in a given field.
3) The blue circles represent AI knowledge acquired through various expert systems engineering, machine learning, deep learning, reinforcement learning, and other algorithms through which AI models are trained. AI knowledge comes because of the complexity AI can navigate and make sense of. The more complex an AI system and architecture is, the more rules, predictions, recommendations, and decisions it can take on its own, and consequently the more sophisticated its knowledge artefacts are.

For every scenario, we suggest one case study of a H-AI-C, for scenarios 1-3 the cases are real and for scenario 4 it is imaginary, and we develop characteristics of human and AI agents, as well as restraints on AI-Opportunism in knowledge asymmetry (Table 1).

The possible restraints are (Sharma, 1997):

1) Self-Control,
2) Community Control,
3) Client Control, and
4) Bureaucratic Control.

The proposed scenarios are not exhaustive, and are based on the scope what algorithms can know and do today: from very specialised and restricted knowledge and capabilities to an artificial general intelligence (AGI) that can potentially be limitless in knowledge and capabilities.

| | |
|---|---|
| **Scenario** | **1** |
| **Case** | **Intelligent virtual assistant in hospitals**[1] |
| **Characteristics of human agents** | • More knowledge of the domain,<br>• Relies on AI to render processes seamless for patients. |
| **Characteristics of the machine agents** | • Specialised and coded knowledge,<br>• Dependent on humans to tell it what to do. |
| **Restraints on machine opportunism** | • Knowledge asymmetry in favour of humans<br>• Self-control explicitly coded into it,<br>• Client control from the patients,<br>• Bureaucratic control from the doctors and system administrators. |
| **Scenario** | **2** |
| **Case** | **Predix by GE Digital**[2] |
| **Characteristics of human agents** | • Knows more than the machine in some aspects of the domain<br>• Needs to rust the directives of AI. |
| **Characteristics of the machine agents** | • Knows more than humans in some aspects of the domain,<br>• Specialised knowledge explicitly coded<br>• Probabilistic approaches to derive new knowledge,<br>• Relies on humans to validate some of its decisions. |
| **Restraints on machine opportunism** | • Self-control explicitly coded into it,<br>• Client control from other humans, and dependent machinery,<br>• Bureaucratic control from system engineers. |
| **Scenario** | **3** |
| **Case** | **Aladdin by BlackRock**[3] |
| **Characteristics of human agents** | • Knows significantly less than the machine, yet has some areas they master better, |

| | |
|---|---|
| | • Heavily trusts and relies on the machine to make decisions. |
| **Characteristics of the machine agents** | • Knows more than humans in most aspects of the domain,<br>• Analysed large quantities of data to reach robust models that humans may not understand,<br>• May rely on humans to validate the most important decisions. |
| **Restraints on machine opportunism** | • Knowledge asymmetry in favour of AI,<br>• Clients of Blackrock could apply control on Aladdin; however, this control depends on their knowledge about the field, and it can rather be limited, |
| **Scenario** | **4** |
| **Case** | **AGI for large organisations (Imaginary case)** |
| **Characteristics of human agents** | • Considered as a resource to be employed by AGI,<br>• Relies on AI in respect to every decision he makes, |
| **Characteristics of the machine agents** | • Knows significantly more than humans in the domain of expertise and in other domains,<br>• Understands human implicit rules and knowledge,<br>• May rely on humans to keep it plugged |
| **Restraints on machine opportunism** | • Knowledge asymmetry largely in favour of AI, |

**Table 1. Practical cases of ethical issues due to knowledge asymmetry in Human-AI Collaboration**

## Key ethical issues of the collaborative scenarios

The first key point in the scenarios is how the more AI is knowledgeable in a certain domain of expertise, the more powerful it becomes. If we compare for instance scenario 1 with scenario 3 (AI virtual assistant in hospitals vs. BlackRock Aladdin), we see that AI in scenario 3 deals with more complexity, some of which a single human could never manage on her own (managing 7% of the world's financial assets, i.e., over 9 times France's GDP) while AI in scenario 1 simulates tasks that a human assistant can do. In contrast, while AI in scenario 2 can manage tasks that a human agent couldn't achieve (modelling, monitoring, and managing assets of factories through a digital-twin model), it is open to human intervention, since it is humans who perform maintenance tasks and decide whether to consider the system's recommendations. Hence, when AI acquires more knowledge and more ability to deal with a kind of complexity that is foreign to humans, it leaves them less flexibility and less freedom to choose. Human agents are compelled to trust the decisions (or recommendations) of AI, which becomes the expert. It was the case with Aladdin, wherein BlackRock laid off several of its funds and assets managers once Aladdin started showing promising results (NYT, 2017). However, there is no information on Aladdin's ability to explain its decisions nor whether it can teach other humans (or systems) what it is doing. Aladdin is in a position to take away know-how from other asset managers, with the risk of losing every piece of knowledge if it ever crashes or missteps.

Aladdin, and other algorithms that might fit in scenario 3 are examples of AI taking charge of activities requiring highly specialised know-how from humans. Humans in this case become supervisors, managers, and owners of the algorithms, with little to no understanding of what the algorithm is doing, hence becoming vulnerable agents, or ***"alienated super-masters"*** of the machines (Coeckelbergh, 2015). In this vein, the question to be raised is how far are we as individuals, a society and a human race ready to delegate more crucial responsibilities such as healthcare, to algorithms? Can we implement control systems to render humans less alienated and more informed super-masters of the machines?

The answer for us lies in a narrow collaboration between AI and humans, where AI is expected to interact with experts and share its knowledge and insights with them. While the terms and modalities of such a collaboration are yet to be defined, we believe that it is fundamental to focus our future research endeavours in this direction. We believe medicine and healthcare in a broader sense to be one professional context which should benefit from more attention since AI decisions directly impact the lives of human beings. Many studies are proposing the need for the involvement of healthcare professionals and clear transparency in all the steps leading to and during the introduction and usage of powerful algorithms into the healthcare industry (Cai et al., 2019; Park et al., 2019).

## Conclusion

The encroaching ubiquity of AI, its potential impact in all areas of life and the increasing expectations for humans and AI systems to work jointly in hybrid organisations, is highlighting the need for ethical concerns to be placed at the front and centre of AI research and implementation in practice. In this paper, we argued that part of the ethical concerns surrounding Human-AI collaboration can be analysed through the lens of knowledge asymmetry between human agents and machine agents. The initial findings of our cursory literature review led us to suggest four collaborative scenarios following the spectrum of AI capabilities (from average to all-powerful). Future research in the field should be directed towards understanding knowledge transfer between humans and AI in ways to mitigate the current growing knowledge asymmetry in favour of AI.

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