AI-empowered KM processes for decision-making: empirical evidence from worldwide organisations

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Abstract

Purpose – *This paper aims to provide empirical evidence on adopting artificial intelligence (AI), including generative AI, in knowledge management (KM) processes and its impact on organisational decision-making. Specifically, the study addresses three key research questions:* RQ1: *How is (generative) AI adopted within KM processes in organisations?* RQ2: *What factors influence the adoption of AI in these processes, either facilitating or inhibiting it? RQ3: How does AI adoption in KM processes affect organisational decision-making?*

Design/methodology/approach – *An explorative investigation has been conducted through semi-structured interviews with KM and AI experts from a worldwide sample of 52 mostly private, large and for-profit organisations. Interviews have been analysed through a mixed thematic analysis.*

Findings – *The study provides an original framework in which the three investigated concepts are interconnected according to a dual relationship: linear and retroactive and 20 factors affecting AI adoption within KM processes.*

Practical implications – *The provided model guides managers in improving their organisational decision-making through AI adoption in KM processes. Moreover, according to the rational decision-making model, the authors propose a six-step systematic procedure for managers.*

Originality/value – *To the best of the authors' knowledge, this is the first study that simultaneously addresses AI, KM and decision-making and provides an integrated framework showing the relationships between them, allowing organisations to better and practically understand how to ameliorate their decision-making through AI adoption in KM processes.*

Keywords *Artificial intelligence, Knowledge management, Decision-making, Framework, Thematic analysis*

Paper type *Research paper*

1. Introduction

In the past, organisations struggled with the lack of data; nowadays – and even more in the future – they (will) struggle to handle its copiousness because the capacity to generate and collect data is rising exponentially (Bag *et al.*, 2021; Justy *et al.*, 2023; Mortati *et al.*, 2023; Rothberg and Erickson, 2017). However, on average, 55% of this data are "dark": they go unused because they are unknown (Splunk, 2019). Thus, a growing need has emerged to help organisations understand what to do with this massive amount of data and how to use it best to make more informed and, theoretically, fairer decisions (OECD, 2022; Yunita *et al.*, 2022).

In fact, all this data significantly impacts organisations' knowledge management (KM), understood as the process of identifying, organising, storing and disseminating data/information/knowledge within an organisation (Beesley and Cooper, 2008; Heisig, 2009). Traditional KM cannot process and analyse this massive amount of data effectively, enabling better decisions (Chierici *et al.*, 2018). Thus, organisations are called to revise their KM models and processes (Chirumalla, 2013; Liu *et al.*, 2023) to better collect, transform

and use the new and copious available data (Manesh *et al.*, 2020), ensuring positive impacts on their performance and competitiveness (Del Giudice *et al.*, 2023; Lee *et al.*, 2020).

In this vein, artificial intelligence (AI) seems to help ameliorate KM processes (Dragičević *et al.*, 2022; Leoni *et al.*, 2022; Sanzogni *et al.*, 2017); thanks to its ability to acquire, process and use knowledge to perform tasks as well as its capacity to reduce uncertainty and unlock knowledge that can be delivered to humans to improve decision-making (Gupta *et al.*, 2022; Haenlein and Kaplan, 2019), with positive impacts on the overall firm performance (Mikalef and Gupta, 2021). In other words, AI may "support decision-making and knowledge management" (Brock and von Wangenheim, 2019, p. 115), creating more effective, accurate and flexible organisational decisions (Agrawal *et al.*, 2017a; Metcalf *et al.*, 2019; Wilson and Daugherty, 2018). This is even more true if we consider the emergence of generative AI tools (like ChatGPT, GitHub Copilot and AlphaCode), which are leading in a new KM era by revolutionising the way knowledge is generated, synthesised and applied (Alavi *et al.*, 2024).

However, the relevance of KM literature and its integration with AI advancements has often been overlooked. It is observed that there exist certain unexplored areas regarding the results, obstacles and constraints associated with the implementation of AI within KM processes in contemporary organisations' decision-making (Al Mansoori *et al.*, 2021; Oppioli *et al.*, 2023; Trunk *et al.*, 2020). In fact, although numerous studies have highlighted the enhancements AI brings to KM in areas like knowledge acquisition and problem-solving, there is a significant gap in understanding the full spectrum of AI applications within all KM processes. This includes a lack of comprehensive strategies for integrating AI into KM processes (Taherdoost and Madanchian, 2023) and insufficient research on how AI adoption affects knowledge workers (Budhwar *et al.*, 2022) both in terms of opportunities (e.g. improving individual performance, reinventing talent management practices) (Claus, 2019; Malik *et al.*, 2023a) and challenges/concerns (e.g. risks related to well-being, bias, privacy issues, ethical dilemmas, etc.) (Budhwar *et al.*, 2022). This underscores the need for a deeper exploration of how AI technologies, particularly generative AI – integrated with KM processes – operate at both individual knowledge workers and organisational levels (Davenport, 2007), influencing organisational decision-making and outcomes (Kudyba *et al.*, 2020; Davenport *et al.*, 2022).

Furthermore, many studies only discuss (generative) AI's potential in KM (Liebowitz, 2001; Jarrahi *et al.*, 2023; Alavi *et al.*, 2024) and, with specific reference to knowledge workers, many of them (Budhwar *et al.*, 2022; Malik *et al.*, 2023b) provide frameworks belonging to systematic literature reviews, thus highlighting the need for more first-hand-based research. In this vein, Pauleen and Wang (2017) and Korzynski *et al.* (2023) call for further empirical research investigating AI adoption within KM processes to ameliorate organisational decision-making, along with the elements that contribute to or hinder such adoption (Kinkel *et al.*, 2022).

Thus, this paper aims to answer the following research questions:

RQ1. How is (generative) AI adopted within KM processes in organisations?

RQ2. What elements favour or inhibit (i.e. influencing factors) this adoption?

RQ3. How does AI adoption in KM processes impact organisational decision-making?

To answer these questions, an explorative investigation has been conducted through semi-structured interviews with KM and AI experts – which represent the unit of analysis of this research – from a worldwide sample of 52 organisations, mostly private (86.5%), large (61.5%) and for-profit (92.3%) organisations, belonging mainly to the following sectors: ICT/IT service and consulting (19.2%), consulting (17.3%), financial service (7.7%), hospitality

(5.8%), retail (5.8%) and transport (5.8%). Interviews have been analysed through a mixed thematic analysis.

The study provides an original framework in which the three investigated concepts are interconnected according to a dual relationship: linear and retroactive and 20 influencing factors related to AI adoption within KM processes. Accordingly, specific managerial guidelines are provided for improving organisational decision-making through AI adoption in KM processes.

The rest of the paper is structured as follows. In Section 2, the theoretical background is presented by focusing on the role of AI within KM processes and on the role of AI-empowered KM processes in companies' decision-making processes. Section 3 reports the research design, data collection and data analysis of the proposed investigation. Section 4 is devoted to the findings, which have been used to develop an integrated framework synthesising the phenomena under investigation, as reported in Section 5, together with theoretical and practical implications. Finally, Section 5 presents the study's conclusions, main limitations and possible future directions.

2. Theoretical background

2.1 Role of artificial intelligence in knowledge management processes

In today's rapidly evolving era, characterised by uncertainty and dynamism, organisations increasingly recognise the importance of implementing digital technologies to effectively manage their knowledge processes (Al Mansoori *et al.*, 2021; De Bem Machado *et al.*, 2021). Indeed, KM processes – as identified by Heisig (2009) – focus on the processes related to the identification, acquisition, creation, storage, sharing and application of valuable knowledge for the organisation (Alavi and Leidner, 2001). Thus, organisations are exploring how KM processes can be combined with new digital technologies to ameliorate the processes themselves as well as the organisation's overall performance (Gao *et al.*, 2021; Husain and Ermine, 2021; Leoni *et al.*, 2022). Consequently, technology has acquired an increasingly central role in the KM domain (Bhatt, 2001; Geisler and Wickramasinghe, 2015), enabling people to broaden the knowledge spectrum and make it accessible to everyone, anywhere, anytime (Al Mansoori *et al.*, 2021).

In this context, AI stands out as the most prominently studied and focused upon digital technologies, garnering unparalleled interest for its role in enhancing KM processes (Husain and Ermine, 2021; Leoni *et al.*, 2022). Basically, AI gives computers the ability to perform cognitive functions usually occurring within the human brain (such as reasoning and learning), solving complex problems previously tackled by human experts (Lei and Wang, 2020). By doing so, AI may reveal (or unlock) new knowledge from vast quantities of data that can be delivered to humans to improve their decision-making (Paschen *et al.*, 2020; Vajpayee and Ramachandran, 2019).

Hence, according to Al Mansoori *et al.* (2021) and Bencsik (2021), there is a close mutual interaction between AI and KM, where AI adoption can effectively take KM to the next level. Indeed, AI can be used to recognise patterns and correlations between two or more data sets, and it may provide organisations with intelligent agents for various operations such as user profiling, pattern matching and text mining (Al Mansoori *et al.*, 2021; Sundaresan and Zhang, 2022). Moreover, thanks to the prediction capabilities of AI-based technologies, it is possible to make assumptions about how future events might affect organisations (Ganesh and Kalpana, 2022; Jauhar *et al.*, 2023), facilitating predictive analytics for risk assessment, machine learning algorithms to adapt to fluctuating market dynamics and intelligent automation to increase efficiency (Ivanov, 2023; Zamani *et al.*, 2022).

The disruptive role of AI in KM processes is even more evident if we consider generative AI tools (Korzynski *et al.*, 2023). These tools can take raw data and "learn" to produce various

types of content, including text, imagery and audio (Harreis *et al.*, 2023), enabling people to broaden the knowledge spectrum and make it accessible to everyone, anywhere, anytime (Al Mansoori *et al.*, 2021), making KM processes potentially less expensive and more pervasive and powerful (Al-Emran *et al.*, 2018).

However, although the enabling power of (generative) AI in KM processes is widely recognised (Agrawal *et al.*, 2017b; Duan *et al.*, 2019), many studies are centred exclusively on the potential role that (generative) AI may have in KM (Liebowitz, 2001; Jarrahi *et al.*, 2023; Alavi *et al.*, 2024), neglecting empirical evidence. In this vein, it is worth mentioning that some exceptions exist, but they focus on single KM processes. For example, Deng *et al.* (2023) investigate the use of digital technologies in facilitating KM only concerning the knowledge-sharing process, whereas Chin *et al.* (2024) address how AI–human interactions can be interpreted as a knowledge creation system.

Thus, a significant gap exists in understanding the full spectrum of AI applications within all KM processes. Filling this gap represents the first aim of this investigation – *RQ1*: How is (generative) AI adopted within KM processes in organisations?

Furthermore, it is worth noting that despite the recognised benefits deriving from the application of AI in KM processes, there are still many difficulties that organisations encounter in carrying out the effective and efficient implementation of these new tools (Davenport *et al.*, 2020), as well as numerous resistances, especially in terms of AI's positive/negative impacts at both organisational and individual levels (Budhwar *et al.*, 2022; Claus, 2019; Dwivedi *et al.*, 2021; European Commission, 2020).

As clearly stated in the perspectives editorial by Budhwar *et al.* (2023), the outcomes generated by the adoption of AI can be interpreted as two sides of the same coin, i.e. positive and negative, powerfully highlighting the need to understand the broad spectrum of factors that influence its adoption and, therefore, the results achievable (Kinkel *et al.*, 2022). For example, dealing with biased data (i.e. biased AI algorithms), cybersecurity and privacy issues and transformation processes related to the adoption of AI represent crucial challenges (Malik *et al.*, 2021, 2023a).

Accordingly, providing an overview of the factors that promote or hinder AI adoption, with specific reference to KM processes, represents the second aim of this investigation – *RQ2:* What factors influence the adoption of AI in these processes, either facilitating or inhibiting it?

2.2 Artificial intelligence-empowered knowledge management processes in organisations' decision-making

Recent studies highlighted how the integration of AI into KM processes not only accelerates the pace of knowledge dissemination but also enables organisations to ameliorate their decision-making processes (Alshadoodee *et al.*, 2022; Caputo *et al.*, 2023; Oppioli *et al.*, 2023). In fact, AI tools are considered a powerful means to help organisations and individuals achieve better decisions (Nazeer *et al.*, 2023), even more so when generative AI is adopted within KM processes to store, transform and distribute data, information and knowledge (Korzynski *et al.*, 2023). In this vein, Trunk *et al.* (2020) stress the increasing importance of managers' education in properly using AI in decision-making. Moreover, it has been recognised that when decision-making processes are AI-based, they are "more 'informed' because the exchange of information is rapid (often in real-time) [so, they are more] precise, punctual, efficient and valid" (Caputo *et al.*, 2023, p. 2800).

Thus, AI-empowered KM processes improve efficiency in knowledge transmission, capture, storage, analysis, visualisation and interpretation (LaValle *et al.*, 2010; Chen and Zhang, 2014), leveraging the vast amounts of data generated and disseminated through increased automation and big data usage (Carlucci *et al.*, 2020; Iandolo *et al.*, 2021) and revealing valuable insights on which to assist employees at various decision-making levels

(McAfee *et al.*, 2012; Meski *et al.*, 2019), in both private and public sectors (Di Vaio *et al.*, 2022). In sum, AI adoption within KM processes boost organisations' decision-making abilities by making them more effective, accurate and flexible (Agrawal *et al.*, 2017a; Dennehy *et al.*, 2022; Duan *et al.*, 2019; Metcalf *et al.*, 2019).

Despite the above-mentioned positive aspects, it is worth mentioning that how KM processes and AI tools should be combined into KM processes to improve organisations' decision-making processes seem to be still underestimated (Caputo *et al.*, 2019; Chinnaswamy *et al.*, 2018; Russo *et al.*, 2023; Singh and Del Giudice, 2019). In this vein, according to Malik *et al.* (2023b), it is necessary for there to be an interaction between managers and AI to obtain valuable decisions. This interaction can be of different types, considering the numerous concerns (e.g. accuracy, explainability, data privacy/security) related to AI adoption. Thus, there is a need to establish a climate that facilitates human–machine collaboration within KM processes in organisations (EU, 2021; Liebowitz, 2021; Xiong *et al.*, 2022).

However, no clear approaches on organising KM and AI for decision-making are currently provided (Trunk *et al.*, 2020), raising a need for more empirical analyses (Di Vaio *et al.*, 2022). This represents the third and last aim of this investigation – *RQ3*: How does AI adoption in KM processes affect organisational decision-making?

3. Methodology

3.1 Research design

This paper follows a qualitative approach as the best one for describing, interpreting and gaining in-depth insight into the phenomena under investigation (Azungah, 2018; Cao *et al.*, 2021) and because it has already proven to be valid for similar studies (Mortati *et al.*, 2023).

To collect primary data, semi-structured interviews at a distance (Saarijärvi and Bratt, 2021; Seidman, 2006) were conducted with KM and AI experts, who constitute the unit of analysis of this research, from 52 worldwide organisations between January 2021 and September 2023. Authors opted for semi-structured interviews as the right compromise between formality and informality. Indeed, this type of interview proves to be flexible, accessible and intelligible (Qu and Dumay, 2011), allowing a guided conversation between researchers and participants thanks to the interview protocol and the possibility for researchers to probe participants for additional details.

The semi-structured interview protocol has been validated through a pilot test (Malmqvist *et al.*, 2019) with three experts. The pilot tests aimed to assess the suitability of the questions and offer early insights into the feasibility of the research. In addition, it allowed the authors involved in the data collection to gain experience in conducting in-depth, semi-structured interviews by further developing their interviewing skills and understanding of conversation flow dynamics.

3.2 Data collection

Two authors have conducted the data collection process due to their direct access to elite informants. To select the interviewees, an email was sent to all the professionals from the two authors' networks who, due to the role held, should have had adequate experience and knowledge in the field of AI, KM and organisational decision-making. The email explained the research project and its main objectives and asked the professional if they were interested in participating in the project. All those who showed interest received a second email containing the basic structure of the interview to verify ex ante the adequacy of their position and knowledge concerning the topics that would have been addressed in the interview itself. After this second email, 52 professionals confirmed their willingness to join the project and were interviewed. According to Guest *et al.* (2006), concept of data

saturation – i.e. the idea that additional interviews become redundant if they only reiterate what is already been learned from prior interviews – the authors felt to have reached this threshold with the 49th interview. Nonetheless, three extra interviews were conducted to confirm that no additional insights were missed.

Recognising the potential for self-selection bias – where companies willing to participate might systematically differ from those unwilling – we implemented proactive measures to mitigate this risk. Invitations to participate were extended to various experts and incentives were offered to encourage participation. These incentives included the promise of a report on the main research findings and a reserved place at a closed-door dissemination workshop. This approach aimed to minimise the likelihood that only certain types of experts would respond, thereby enhancing the diversity and representativeness of our sample (Groves *et al.*, 2009).

The interview protocol was organised into five parts (Castillo-Montoya, 2016): participants were informed about the study aim; authors interviewed respondents starting with demographic questions (e.g. their specific job role, the year of experience); the interviews shifted towards more study-objective specific questions; participants were encouraged to provide examples; and participants were invited to provide additional comments.

All interviews were conducted online, digitally recorded, transcribed and translated (when necessary) from Italian into English by the authors to ensure consistency and avoid language bias. Moreover, all transcripts were merged to build a unique data set and triangulated with corporate documents, press articles and other publicly available materials.

Each participant signed an interview release form in which they specified whether the authors were authorised to use their organisation's name. Moreover, each of them received the transcript of their interview "principally to validate what was said during the interviews [. . .] or discover and correct errors or inconsistencies" (Mero-Jaffe, 2011, p. 236).

It is worth underlining that, of the 52 interviewed, most of them belong to large (61.5% with more than 1,000 employees), private (86.5%) and for-profit (92.3%) organisations. In comparison, only six (11.5%) belong to public organisations and only one (1.9%) to an intergovernmental agency. In terms of years of activity, the average is 15.2 years, whereas, in terms of role, most of them are knowledge manager (23%), digital innovation/solutions/transformation manager/head (15.4%) and CEO/found/owner (15.4%); thus, they demonstrate adequate experience in terms of KM, AI and decision-making. Finally, the participants belong to organisations mainly in the following sectors: ICT/IT service and consulting (19.2%), consulting (17.3%), financial service (7.7%), hospitality (5.8%), retail (5.8%) and transport (5.8%).

Table 1 provides further details on the type of informants and related organisations.

3.3 Data analysis

A *verbatim* transcription process was carried out for all the interviews to improve the research's reliability, validity and trustworthiness (MacLean *et al.*, 2004). The analysis of transcripts – and the triangulation with other sources – has been conducted through a mixed thematic method (Braun and Clarke, 2006; Clarke and Braun, 2017; Yin, 2014), drawing from both deductive analysis, in which communication messages are categorised according to an initial codebook, and inductive analysis, where new themes are allowed to emerge. According to the research questions and the theoretical foundation of this study, the already identified KM processes have been used as the initial codebook for the deductive analysis.

Three authors took part in the analysis process, identifying and categorising all the relevant information in the interviews' transcripts according to specific steps (Knox *et al.*, 2021). In the first step, each participant's transcript was individually examined to obtain the first-order

Table 1 Interview details (in alphabetical order by organisation name)

#	Interviewee role	Interviewee's years of activity	Organisation name*	Country of reference**	Organisation sector	Organisation typology	Foundation year	Company size (n. of employees)	Interview duration***
1	Founder and CEO	22	36Brains	Italy	Business intelligence and investigation	Private (for-profit)	2020	<10	1 h 34 min
2	Knowledge engineering manager	7	Amazon	USA	Retail	Private (for-profit)	1994	>1,000	59 min
3	Senior expert in data and AI solution	24	Avanade Italia	Italy	IT consulting	Private (for-profit)	2000	>1,000	1 h 31 min
4	Digital transformation & senior consultant	12	BIP	Brazil	Consulting	Private (for-profit)	2003	>1,000	1 h 53 min
5	Consultant	9	Capgemini	China	IT services and consulting	Private (for-profit)	1967	>1,000	48 min
6	IT project manager	8	Consorzio Bioingegneria e Informatica Medica – CBIM	Italy	IT services and consulting	Public (non-profit)	1992	<10	1 h 23 min
7	Managing partner	7	COREangels Climate	Spain	Financial services	Private (for-profit)	2023	<10	1 h 48 min
8	Data centre sales engineer	27	Dell Technologies	Italy	ICT	Private (for-profit)	1984	>1,000	1 h 35 min
9	Senior consultant	8	Deloitte	Canada	Consulting	Private (for-profit)	1845	>1,000	1 h 33 min
10	Head of people digital hub	22	Enel	Italy	Energy and utilities	Mostly public (for-profit)	1962	>1,000	1 h 30 min
11	HR recruitment, selection & orientation	5	FAC Services	USA	Professional services	Private (for-profit)	2005	<250	1 h 12 min
12	Junior category manager	3	Findus Italia	Italy	Food	Private (for-profit)	1964	<250	56 min
13	Founder & owner	11	GuruScan	The Netherlands	ICT	Private (for-profit)	2008	<50	1 h 21 min
14	Knowledge solutions architect and founder	21	Heuristica	Switzerland	Technology	Private (for-profit)	2020	<10	1h 25 m
15	Assistant manager	5	KPMG	UK	Consulting	Private (for-profit)	1958	>1,000	1 h 00 min
16	Knowledge transfer manager	23	Ministero dello Sviluppo Economico	Italy	Public services	Public (non-profit)	2013	>1,000	1 h 17 min
17	CEO	8	Peekaboo	Italy	Consulting	Private (for-profit)	2015	<10	1 h 45 min
18	Founder and owner	25	Publiwork Service	Italy	Professional services	Private (for-profit)	2002	<10	50 min
19	Knowledge manager	12	Renault	France	Automotive	Private (for-profit)	1898	>1,000	1 h 54 min
20	Organization manager	17	SEA Milan Airports	Italy	Transport	Private (for-profit)	1958	>1,000	56 min
21	Software solutions analyst	2	Sogei	Italy	ICT	Public (for-profit)	1976	>1,000	1 h 10 min
22	HR manager	5	Soho House & co.	UK	Hospitality	Private (for-profit)	1995	>1,000	1 h 00 min
23	Digital innovation manager	21	Techno Center	Italy	ICT	Private (for-profit)	2007	<200	1 h 39 min
24	Data analyst	15	Trenitalia	Italy	Transport	Public (for-profit)	2000	>1,000	1 h 52 min
25	Customer assistant	3	Unicredit	Germany	Financial services	Private (for-profit)	1879	>1,000	1 h 05 min
26	Knowledge development manager	14	Unifarco	Italy	Health care	Private (for-profit)	1982	<500	57 min
27	Data scientist	3	WhereTech	Italy	IT services and consulting	Private (for-profit)	2020	<50	1 h 07 min
28	Project leader	7	Wolters Kluwer	China	IT services and consulting	Private (for-profit)	1836	>1,000	53 min

(*continued*)

Table 1

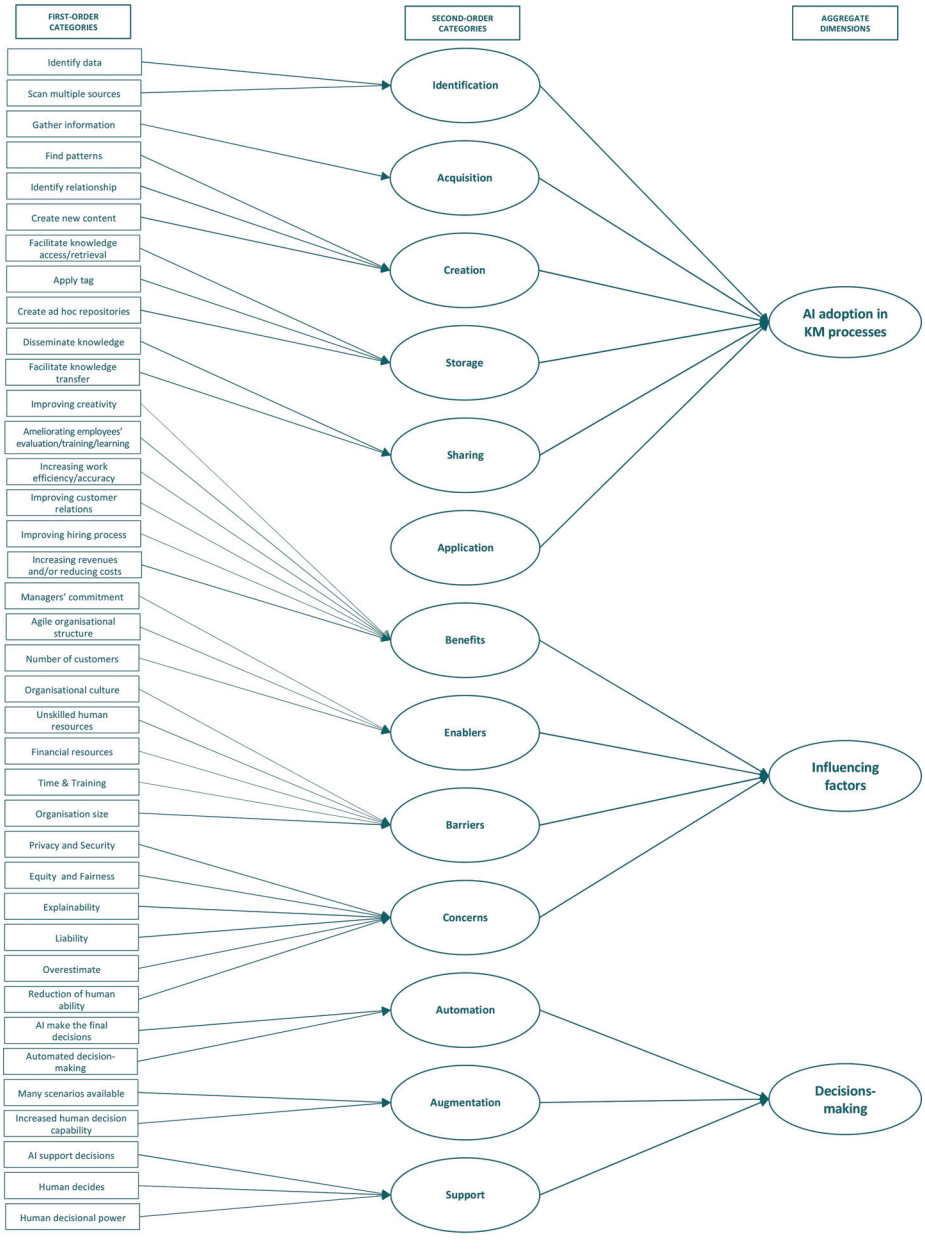
#	Interviewee role	Interviewee's years of activity	Organisation name*	Country of reference**	Organisation sector	Organisation typology	Foundation year	Company size (n. of employees)	Interview duration***
29	Senior knowledge management specialist	27	n.a.	Canada	International Trade and Development	Intergovernmental agency (non-profit)	1944	>1,000	1 h 37 min
30	Head of knowledge and IP	13	n.a.	Germany	Consulting	Private	1996	>1,000	48 min
31	Knowledge manager	10	n.a.	USA	Consulting and technology	Private (for-profit)	1965	>1,000	1 h 16 min
32	HR director	20	n.a.	USA	Leisure facilities and services	Private (for-profit)	1999	>1,000	1 h 16 min
33	R&D projects and knowledge management	15	n.a.	USA	Automotive	Private (for-profit)	1872	>1,000	1 h 15 min
34	Digital healthcare and innovation head	28	n.a.	Italy	Chemical and pharmaceutical e health care	Private (for-profit)	1982	<500	1 h 31 min
35	Director	28	n.a.	Italy	Consulting	Private (for-profit)	2006	<250	27 min
36	Knowledge management engineer	21	n.a.	The Netherlands	Aerospace, science and research	Private organisation for an intergovernmental agency**** (non-profit)	1982	<300	1 h 30 min
37	Senior manager digital business transformation	21	n.a.	Switzerland	Chemical/Health Nutrition	Private (for-profit)	1902	>1,000	1 h 26 min
38	Co-founder	20	n.a.	Brazil	Advertising services	Private (for-profit)	2020	<10	1 h 07 min
39	Talent management consultant	10	n.a.	Brazil	Education	Private (for-profit)	1948	>1,000	1 h 00 min
40	Fraud and security intelligence specialist	30	n.a.	USA	ICT	Private (for-profit)	1987	<500	53 min
41	Digital transformation consultant	12	n.a.	USA	Aerospace	Private (for-profit)	1916	>1,000	1 h 41 min
42	Knowledge manager	9	n.a.	France	Health care	Private (for-profit)	2018	<500	1 h 19 min
43	Data analyst	4	n.a.	France	Financial services	Private (for-profit)	1890	>1,000	1 h 22 min
44	R&D projects manager	23	n.a.	Italy	Hospitality	Private (for-profit)	1937	>1,000	1 h 37 min
45	HR manager	6	n.a.	Germany	Education	Private (for-profit)	1982	>1,000	43 min
46	Digital solutions developer	18	n.a.	Spain	Consulting	Private (for-profit)	1998	>1,000	58 min
47	Digital innovation manager	18	n.a.	Spain	Transport	Private (for-profit)	1977	<50	1 h 26 min
48	CEO	13	n.a.	UK	Retail	Private (for-profit)	1962	>1,000	1 h 13 min
49	Digital and innovation head	25	n.a.	UK	Hospitality	Private (for-profit)	1982	<250	1 h 47 min
50	Senior knowledge manager	14	n.a.	USA	Financial services	Private (for-profit)	1816	>1,000	1 h 33 min
51	Senior expert in AI	30	n.a.	USA	Consulting	Private (for-profit)	1926	>1,000	1 h 55 min
52	CEO	29	n.a.	Italy	Retail	Private (for-profit)	1967	>1,000	1 h 06 min

Notes: *If the interviewee has not given his/her consent to use the organisation name, "n.a." (i.e. not applicable) has been entered in the reference column; **Regardless of the country in which the interviewee operates, the impact of his/her functions/actions/decisions is reflected, in most cases, in all countries in which the organiaation operates; ***For convenience, the duration of the interviews has been rounded to the nearest minute; ****Please note that the intergovernmental agency was established in 1975 and has over 1,000 employees

Source: Authors' own work

codes (Spiggle, 1994). A "multiple rater" approach was used (Scandura and Williams, 2000); thus, the authors analysed transcripts individually, and when disagreeing, they deepened the analysis to find a shared vision. In the second step, the authors grouped codes into second-order constructs, i.e. categories and categories into themes based on content analogies and affinity, to identify common patterns and differences. In the final step, the authors extrapolated a unified model synthesising how (generative) AI adopted within KM processes affect organisational decision-making. An extract of how the thematic analysis was conducted is shown in Figure 1.

Figure 1 Thematic analysis



Source: Authors' own work

4. Findings

4.1 Artificial intelligence adoption in knowledge management processes

All the different interviewees confirmed the crucial role that AI is currently playing in KM processes within their organisations. They state that AI is nowadays indispensable to carry out KM processes for three main reasons: the number of collectable data and information has increased in a potentially infinite way, it is unthinkable that humans can perform the analysis, integration, dissemination and storage of this infinite variety effectively and efficiently in space and time and the organisation's overall performance is ameliorated thanks to the possibility to make better decisions through the application of AI-enhanced knowledge. Thus, according to interviews, (generative) AI pervades all KM processes, playing a crucial role in organisational decision-making (Table 2).

Adopting (generative) AI within KM processes is far from simple. In this respect, interviewees emphasise that, to choose an AI tool, the organisation must make careful and multiple analyses without being "exclusively" influenced by current trends. In other words, what kind and how many AI tools an organisation has to adopt can be understood as a wise balance between multiple influencing factors (as detailed below).

4.2 Influencing factors

4.2.1 Benefits. The first factor that strongly emerged from the interviews and which "justifies" the increasingly massive adoption of AI by organisations refers to the benefits that this use brings (or at least should bring) to the organisations. According to the different interviews, six benefits can be identified, as reported in Table 3.

What interestingly emerges from Table 3 is that using AI improves organisations from a double aspect. From an *operational point of view*, AI within KM processes allow organisations to reduce the time and cost of carrying out tasks. In this vein, when tasks are performed in real time, organisations can identify patterns, trends and anomalies as they emerge, making decisions on up-to-date information. According to interviewees, this real-time processing enhances operational efficiency, allowing organisations to know immediately where they need to allocate resources; improves customer experience, allowing organisations to anticipate customers' needs and/or adjust their product/service accordingly; and ameliorates risk management, allowing organisations to identify potential risks before they impact business operations. From a *cognitive point of view*, AI adoption can act as a stimulus for humans, allowing individuals/employees to increase their potential (by learning more and better, improving their creativity, and the like), which in turn benefits the organisation.

4.2.2 Enablers. Interviews highlighted three main AI enablers (Table 4) and the most important one is the employees' – especially managers' – commitment. In this respect, several managers' crucial activities have been underlined, such as the importance of organising the "AI journey" according to a double perspective, i.e. top-down and bottom-up, to ensure the organisation as a whole has the opportunity to understand better how (the method) and why (the scope) the new AI tools will be adopted, as well as the possibility to express their opinion on the matter. It is also essential that managers are fully aware of the time required for the transformations linked to using AI tools to be fully implemented and thus bring about the expected results. In other words, an agile organisational structure is essential.

It is worth mentioning that, among the enablers, the number of customers also emerges. In this respect, the increase in the number of customers provides a larger data set for an organisation, enhancing the effectiveness of AI adoption that can enable more accurate predictions and personalised recommendations. In addition, a more extensive customer base often means more resources, facilitating investment in AI technologies and expertise. Finally, leveraging AI with a more extensive customer base enables organisations to

Table 2 Role of (generative) AI within KM processes

KM process	*AI role*	*Quotes*
Identification	■ Data collection and processing: AI can automate the gathering and analysis of large data sets, reducing the need for extensive human involvement and increasing efficiency ■ Pattern recognition and insight generation: AI tools can uncover hidden patterns within data, leading to new insights that can significantly influence decision-making processes ■ Market trend analysis: AI's ability to detect key, emerging trends and shifts in the market in real time suggests its application in dynamic market analysis, helping organizations respond swiftly to changes, anticipating market movements and customer needs, thus facilitating proactive strategy adjustments	"I have to draw more and more data, and to do it, either I put many people to carry out this task, or I put robots to do this for me. In this sense, AI is perfect" [Interview #7] "Generative AI tools have been instrumental in identifying hidden patterns within our data, providing invaluable insights that were previously overlooked, with important effects on our decision-making processes" [Interview #31] "Through the use of AI, we've enhanced our ability to identify key trends and market shifts in real-time" [Interview #37] "With the help of AI-driven analytics, we were able to identify emerging market trends and customer preferences hidden within vast amounts of unstructured data. This allowed us to stay ahead of the curve and adapt our strategies proactively" [Interview #52]
Acquisition	■ Knowledge acquisition efficiency: AI, particularly generative tools, enhances the efficiency of extracting relevant information from varied sources, facilitating data-driven decision-making ■ Text mining: AI-powered text mining systems transform the process of gathering information from scientific literature and industry reports, boosting efficiency and accelerating innovation ■ Customer insights and engagement: AI applications like text recognition and augmented analytics allow for the detailed analysis of online mentions of a company, aiding in better customer acquisition, retention and service	"Generative AI tools have streamlined our knowledge acquisition process, enabling us to extract relevant information from diverse sources efficiently, empowering my team to make data-driven decisions" [Interview #40] "Our AI-powered text mining system has revolutionised how we gather information from scientific literature and industry reports. It has significantly reduced the time and effort required to collect relevant data, empowering our R&D teams to accelerate innovation" [Interview #42] "We've accelerated our knowledge acquisition efforts" [Interview #47] "Through AI tools such as text recognition and augmented analytics, we can analyse the data on how our company is mentioned online; this helped us to acquire, retain and serve better our customers" [Interview #51]
Creation	■ Idea and solution innovation: AI aids in generating novel ideas and solutions, fostering innovation within organizations ■ Creative content generation: the use of (generative) AI enables the rapid creation of creative content capable of positively impacting customer engagement and satisfaction	"We use AI tools to organise and manage information within our company, find patterns, trends, and relationships between them. This has a positive impact on our decision capability" [Interview #12] "AI assist us in generating innovative ideas and solutions" [Interview #25] "In [name of the organisation], we use many AI tools – for image recognition, semantic search, and the like – to perform multiple tasks, like data analysis and content creation" [Interview #31] "Through the use of generative AI, we can generate creative content and solutions at unprecedented speed, with positive effects on our customers" [Interview #38]
Storage	■ Storage infrastructure transformation: AI has been pivotal in overhauling knowledge storage infrastructures, leading to the development of centralized repositories that ensure efficient access to vital insights, revolutionising knowledge storage, streamlining the organisation and retrieval of vast data sets, thereby enhancing organizational decision-making processes	"Generative AI tools modernised our knowledge storage capabilities, allowing us to organize and retrieve vast amounts of information more efficiently and positively impacting decision-making across our organization" [Interview #15] "We use Neural Network Services for classifying texts, images, and sounds, and they can be adopted in many KM processes. For example, the AI tools that allow us to classify text properly come into play on several occasions: when we need to create knowledge or when we must use what we already have [in terms of data, knowledge] in the company or when we have to storage data and information" [Interview #23]

(*continued*)

Table 2

KM process	*AI role*	*Quotes*
Sharing	■ Facilitation of knowledge sharing: AI significantly boosts knowledge sharing among teams, ensuring swift distribution of insights and best practices, which in turn enhances decision-making and expedites innovation ■ Real-time support: AI offers instant support and guidance to employees and customers, fostering a more informed and responsive organizational environment	"Thanks to AI, we've transformed our knowledge storage infrastructure, creating a centralized repository that facilitates easy access to critical insights" [Interview #30] "Through the use of AI, we've enhanced knowledge sharing across teams, enabling rapid dissemination of insights and best practices. All of this has improved our decision-making and accelerated our pace of innovation" [Interview #34] "AI-driven chatbots enhance our knowledge sharing by providing real-time support and guidance both to our employees and customers" [Interview #47]
Application	■ Decision-making support: AI supports decision-making by integrating data-driven insights into the decision-making framework ■ Routine automation: AI optimizes knowledge application processes by automating routine tasks, thus freeing resources for more strategic activities ■ Predictive analytics: AI allows for anticipating market demand fluctuations, enabling the strategic application of knowledge to optimise decision-making	"Our AI-powered KM processes aid intelligent decision-making" [Interview #5] "Adopting AI in KM helped our organisation to make decisions quickly, efficiently and accurately" [Interview #16] "AI tools simplify our KM process, which makes decision-making faster" [Interview #21] "We decided to invest – and a lot – in AI tools because we believe that the benefit that these bring to our KM processes also spills over into the decisions we make" [Interview #41] "Through AI, we've optimized knowledge application processes, automating routine tasks" [Interview #51] "Through predictive analytics, we've been able to anticipate market demand fluctuations and, thus, properly apply available knowledge, optimising our decisions accordingly" [Interview #51]

Source: Authors' own work

improve decision-making, enhance customer experiences and gain a competitive edge in the market.

4.2.3 Barriers. Respondents acknowledge AI's relevance for KM processes but point out many barriers to its adoption (Table 5). Some of these barriers are typical of any other change/transformation affecting an organisation, such as the "conservative" organisational culture or the lack of adequate financial resources. Different barriers, however, are closely linked to the intrinsic characteristics of AI. In this sense, many interviewees emphasised that one of the most significant barriers to implementing the appropriate AI tools is the presence of unqualified personnel. In this respect, the critical need for organisations to invest in training and development programs to upskill existing employees or recruit qualified professionals emerges. Failure to address this barrier may result in suboptimal utilisation of AI, hindering the organisation's innovation, efficiency and competitiveness.

Another barrier that deserves specific attention regards the organisational size. In this respect, interviews stress how the small company size hinders AI adoption. This could lead to two main consequences: larger organisations – with greater access and capability in using AI – may solidify their dominance in the market, potentially leading to a less competitive landscape, which could result in fewer choices and higher prices for consumers; smaller organisations may struggle to keep up with technological advancements, risking their competitiveness and survival in the market. Therefore, policies and initiatives promoting equal access to technological resources and supporting the development of smaller businesses are crucial for fostering a more balanced and competitive market environment, ultimately benefiting consumers.

Table 3 AI benefits and related quotes

Benefits	*Quotes*
Improving creativity	"Using AI tools allows me to spend my energies better, to concentrate my reasoning and to focus on expanding my creative processes" [Interview #6] "AI ensures that your genius is directly used on the highest value-added part" [Interview #26] "Sometimes the answers that the tool gives are so creative that they somehow teach/educate the interlocutor to seek answers that s/he would otherwise never have thought of and sought" [Interview #34]
Ameliorating employees' evaluation/training/learning	"AI is involved mainly in targeting our courses and experiential learning, like mentoring and coaching, depending on colleagues' individual needs . . . There is an algorithm that, for example, shows those who are the main contributors, those who put in the most papers, those who are the liveliest, those who are the most voted . . . This is obviously useful when we need to have these people be, let's say, also considered according to their commitment, their generosity, their visibility, the feedback they have received" [Interview #10] "You can create personalised learning paths, which are built and cut like a dress according to the specific person. This can clearly only happen with the help of AI, otherwise it would be an unthinkable economic expenditure" [Interview #14] "Through the use of AI, I manage to have an in-depth and updated overview not only of what my teams are doing, but also and above all of how they are doing it, this allows me to understand how to evaluate them but also if and how to help them improve" [Interview #20] "On the training process of medical representatives . . . We invented an AI tool to train medical representatives [that] simulates a doctor with different profiles. The very interesting thing is that the 'doctor' voice changes depending on the interaction it has with the medical representative" [Interview #34]
Improving customer relations	"AI tools allow us to make customer interactions more meaningful and personalised" [Interview #25] "The AI tools we are adopting allow us to acquire greater knowledge about our customers. They provide us with dashboards that allow us to create new products/services that best fit the demand needs . . . A robot in a pharmacy must not only be seen as a very intelligent system that gives you aspirin in a few seconds but also as the AI tool that allows you – while it is taking the medicines – to strike up a conversation with your customer, to understand better his/her need" [Interview #26] "It's like having a 24/7 employee that ensures we're always responsive, and, therefore, in a position to exceed expectations" [Interview #28] "Obviously, the relationship with customers benefits because we are able to get to know them better and, therefore, to satisfy their needs in times and ways that were previously unthinkable" [Interview #48]
Increasing work efficiency/ accuracy	"The integration of AI-powered image recognition technology has enhanced our ability to detect defects and anomalies" [Interview #12] "If AI is present . . . it is possible to discover things that would not have been discovered otherwise. For example: [thanks to AI] we understood that the newsletters sent from Tuesday to Thursday were more effective, rather than those sent on Mondays or Fridays" [Interview #34] "By implementing AI-driven automation in our data entry processes, we've reduced manual errors by 90% and shortened processing times by 50%. This has allowed our team to focus on higher-value tasks, ultimately improving overall productivity" [Interview #42]
Improving hiring process	"The issue was to reduce the screening time because the number of people to be interviewed or brought into the pipeline was particularly high and they wanted to be able to speed up . . . therefore the machine in this sense, not being subject to fatigue gives an evaluation already in the first instance, regardless of the time in which it evaluates the resumes. Obviously, the recruiter intervenes on this and then makes a human assessment." [Interview #3] "The use of AI has allowed us to discover knowledge gaps in some of our departments. This has led us to make new hiring decisions" [Interview #11] "AI does not steal jobs, it generates many. That is, it is generating different specializations" [Interview #26] "AI will open so many jobs" [Interview #34] "AI tool into our recruitment strategy guide us to our ideal candidates" [Interview #39]
Allowing real-time processing	"Through Amazon Go we can detect in real-time which items our customers have picked up from shelves. This enables the store to automatically charge customers for their purchases without going through traditional checkout lines" [Interview #2] "[AI allows] processing the information at the speed that a normal human being could not do" [Interview #29] "If you can automate some processes, you can be faster. So, then you save time, and if you save time, you save resources" [Interview #36] "It saves time because it obviously allows you to search for such a large amount of information in a relatively short time . . . If I am a scientist and, in a day, I can read a hundred articles, artificial intelligence allows me to read more and maybe I can read two hundred a day. In this way, the quality of my output goes up and for the same amount of time I can extract more content and I can extract more relevant information" [Interview #37]

(*continued*)

Table 3

Benefits	*Quotes*
Increasing revenues and/or reducing costs	"We utilise AI to analyse real-time user data and make personalised content recommendations. This improves user engagement and customer retention" [Interview #43] "The possibility of analysing the data as soon as they are available allows you to understand the situation immediately and to be able to act also looking to the future, avoiding the risks that are only potential today actually occur tomorrow" [Interview #50] I think you could definitely reduce costs with AI . . . but always having human decision-making in the loop. I do not think there is a people cost cutting" [Interview #13] "AI allows you to save months, sometimes years, of work that means also save money" [Interview #26] "If two companies, let's say with the same number of staff, one can make its knowledge more productive through AI compared to the other that does not, the value of that company is higher" [Interview #37] "If we exclude the initial expense, certainly and above all in the long term, the AI tools we adopt allow us to reduce some costs by optimising the processes in which they are inserted" [Interview #49]

Source: Authors' own work

4.2.4 Concerns. Participants also pointed out numerous concerns related to AI adoption (Table 6). These concerns are multiple as AI mixes with ethical, moral and legal aspects, making justifying its use and outcomes particularly complex. Several interviewees highlighted how AI can trigger vicious cycles regarding human creativity, destroying it rather than stimulating it. All this brings out again the importance of adopting a conscious approach to the use of AI to exert its benefits to the maximum, reducing threats and challenges to a minimum.

Other concerns that deserve attention are "liability" and "overestimation". Concerning the first aspect, as AI becomes increasingly autonomous, determining responsibility for errors or damaging outcomes becomes complex, potentially leading to legal disputes and

Table 4 AI enablers and related quotes

Enablers	*Quotes*
Managers' commitment	"[It is fundamental] having colleagues' direct involvement and commitment at all the different levels, and large participation in the initial project and design phase" [Interview #10] "It was clear to me right away that it wasn't going to be easy; it was essential to making everyone understand that, despite the obstacles, if we had worked together, we would have achieved important results in the near future." [Interview #19] "The most important is the sponsorship of the company's top management, who make people realise how important it is to invest in knowledge, adopt the logic of digital transformation and explain the value of these solutions" [Interview #34] "Having management commitment, top manager, understanding and supporting AI is key" [Interview #36] "In light of the high investments required to implement the new AI tools, I had to be the first to believe that they would work, that they would allow us to work better, to achieve more. And I believed it, but I had to convince everyone else too!" [Interview #47]
Agile organisational structure	"To fully harness the power of AI tools, our organizational structure must be as agile as the solutions we seek to implement" [Interview #27] "Agile process for implementation . . . it's very important" [Interview #29] "To have a lean and clean organisation, which also has the ability to manage innovation in terms of knowledge with external start-ups and specialised agencies, to facilitate the collaboration process with these, which are often small and therefore need to be approached in a simple manner" [Interview #34] "Adopting AI isn't just about integrating new tools; it's about ensuring our organization's structure is able to evolve with the rapid pace of technological innovation" [Interview #44]
Number of customers	"The volume of our customers is the very catalyst pushing us toward AI adoption, ensuring each of them will be able to receive a tailored experience" [Interview #28] "With our growing customer base, AI tools aren't just an option; they're a necessity!" [Interview #32] "The number of customers to be managed: the higher the number, the more the need to implement a more advanced system arises" [Interview #35]

Source: Authors' own work

Table 5 AI barriers and related quotes

Barriers	*Quotes*
Organisational culture	"In some cases, there is resistance to change that there is fear that AI will replace human beings" [Interview #2] "The most important barrier is the cultural one, which has several sub-aspects and cannot be generalised, there is an aspect related to age, an aspect related to the age of use of devices, but also the general culture in digital transformation and methodology. This also relates to the propensity and adoption of digital transformation by everyone. We annually work on creating and delivering courses to facilitate learning, for example." [Interview #34] "The biggest obstacle is us; Let me explain: if the organisation does not have a proactive orientation towards the use of these new technologies, otherwise it becomes useless even to talk about them" [Interview #40]
Unskilled human resources	"Not having skilled people inside and outside the organization" [Interview #29] "It is easy to find in the US [qualified personnel] . . . especially in the West Cost because there are dedicated schools. When you make the leap to Europe, the availability is halved, but even in this case there is a difference, in fact in Scandinavian and Anglo-Saxon countries, some good figures are easy to find, but you must look for them, if you go down to the Latin countries it is very difficult. In Italy there is something concentrated between Milan (above all) and Rome, southern Italy practically zero" [Interview #34] "You need an AI developer professional that has an eye also on the needs, on the business needs, on the user needs. That's quite difficult to get because AI is quite a specialised area" [Interview #36]
Financial resources	"The problem is that if you convince yourself that AI is cheap stuff and that it works right away, you risk failing miserably; [AI] needs a million images to work, and to work on a million images doesn't cost 100 euros. It's not like everyone can afford [it]" [Interview #3] "There is also an economic factor because the initial investment is not a trivial investment" [Interview #4] "AI is very expensive and [the cost] depends on several factors: the technology we are using, whether you pay per transaction, etc. It is not cheap at all!" [Interview #14] "Budget availability, because these technologies cost money" [Interview #34] "Budget availability, always" [Interview #36]
Time and training	"[AI] may give poor results, but not because the design is wrong, but because the problem has been wrongly posed, or because the data are insufficient" [Interview #3] "Men program AI; so, it's not a problem of AI, it's a problem of who programmed it" [Interview #8] "AI must be trained and improved for a long time to have good results" [Interview #10] "Only if the [AI] system is well configured to collect data, information, and knowledge from different resources and then present it well [AI is useful], otherwise no" [Interview #14] "Implementation time [is a barrier]" [Interview #26] "Unfortunately, it is not easy to set up such technology, and a project takes three to five years, and in that time, technology changes very quickly, and the tool being worked on is perhaps no longer needed" [Interview #34]
Organisation size	"The [small] size of the company is a barrier [for AI adoption]" [Interview #1] "What we are, in terms of size, matters a lot when it comes to AI. In my head, there are many ideas of how AI could help us, but we are still too small to implement certain tools." [Interview #18] "The bigger the ship, the harder it is to change its course! Our organization's size does not make AI tools adoption an easy task" [Interview #52]

Source: Authors' own work

challenges. This is even more true if we consider the current absence of clear regulations and legal frameworks. At the same time, liability concerns could hinder innovation and adoption of AI, slowing down progress in various sectors.

Concerning the second aspect, overestimating AI capabilities can lead to unrealistic expectations and reliance on AI without proper oversight or human intervention, leading to incorrect investments in organisational resources.

4.3 Decision-making

Once AI tools have been identified and the related influencing factors analysed, they are implemented and run accordingly within the different KM processes, aiming to ameliorate the possibility of making decisions that are as accurate, aware, informed and right as possible. In this vein, one of the most exciting aspects that emerges is that – according to participants – decisions can be classified according to the problem they wish to solve (from simple to complex ones). Simple problems deal with every day and frequently occurring difficulties that have established procedures, whereas complex problems encompass

Table 6 AI concerns and related quotes

Concerns	*Quotes*
Privacy and security	"It is clear that you have to understand that if you give Google a document to have it translated, Google will use it for its purposes because it is its business model, in this sense you should be very careful what you share. This is related to the issue of privacy protection, which in Europe is very much focused on the individual, whereas I am much more concerned with the analysis of collective flows. For example: during the first lockdown, Facebook gave anonymised data on the geolocation of the movement that took place that night in Italy (the famous trains that went from the North to the South). It is true that they did not say that Marianna or Ginetta made the trip, but they gave the idea of the mass movement and the next day the government changed a law. It was not an action with zero impact! It is a subject on which one has to be very careful" [Interview #1] "There are AIs that are exploited to defraud man . . . there is software with which I could now present myself to you with the face of another person and with his or her own voice. You would never notice that I'm not myself; so, clearly, it's also a safety factor" [Interview #6] "Ensuring privacy and security isn't just a technological requirement, it is our duty to our employees and customers" [Interview #45]
Equity and fairness	"A question we are often asked is whether the machine has a bias in its choice of CVs. The answer is: absolutely yes, because, I repeat, it is we who give the machine samples and if these have a bias, the machine automatically replicates them . . . However, the recruiter also has the bias, because he is subject to fatigue, and this here creates another type of bias, in my opinion, more dangerous, and therefore the machine in this sense, not being subject to fatigue gives an evaluation already in the first instance, regardless of the time in which it evaluates the resumes. Obviously, the recruiter intervenes on this and then makes a human assessment." [Interview #3] "At European level this problem is being addressed and there is a whole extremely large table on the introduction at European level of regulations for responsible use of AI" [Interview #9] "In theory, the machine has no preconceptions. But the machine responds to criteria that we give it, which are preconceptions" [Interview #10] "If AI use historical data, it may reproduce historical bias" [Interview #13] If we do not realise that we are not talking to a human, this is worrying. If . . . we do not have the 'antibodies' to react, the effect can be dramatic" [Interview #14]
Explainability	"Our ability to understand and trust AI tools decision-making is critical. Without explainability, we're navigating with a black box" [Interview #4] "It's about understanding the 'why' behind [AI tools] decisions. If we cannot interpret the rationale, we risk compromising the integrity of our strategic decisions" [Interview #33] "AI algorithms need to be transparent. When you have an algorithm based on deep learning . . . it's like having a black box . . . you don't understand what it's doing. So, it is very important to introduce AI with awareness, taking care of the ethical and moral aspects. We are in the process of starting our own ethics committee for AI" [Interview #37]
Liability	"Big algorithms can make big mistakes" [Interview #10] "One of my biggest concerns is determining who is responsible for damage caused by an AI-powered device or service. For example, in the case of an accident involving a self-driving car, should the damage be covered by the car owner, the car manufacturer or the software programmer?" [Interview #19] "Autonomy is one of the keys, and this is one of the pitfalls of AI in general: traceability. Can we trace and trace back all the decisions made by an algorithm? Not always. It's especially difficult with neural networks" [Interview #36] "There is a need for clear laws that make it possible to understand if, how and when to assign responsibilities when it comes to AI tools" [Interview #46]
Overestimation	"Another great fear is the excess of expectation that is generated. Since some AI algorithms are available out-of-the-box, it seems that they are easy to implement . . . So you have to go to customers and explain to them that first of all the result is not obvious, an experiment must be carried out to evaluate the effectiveness of the models before adopting it; and that an AI is as prone to errors as a human being" [Interview #3] "AI is quite powerful, but one of the key concerns I have, or I see, is [that it] can be a little bit too powerful for people and organisations if they don't know how to use it. It's like when you just took your driver's license and suddenly ended up in a Lamborghini. It might be a nice car, an expensive car, but you might not be able to use it properly" [Interview #30]
Reduction of human ability	"One of the potential problems is that people get used to using these tools and stop thinking . . . you think the machine has already done everything [. . .] It's true that calculator increases things for you, but if you don't learn to do the calculations yourself, you're missing a piece of the development" [Interview #1] "My main concern is that some people still think that AI can replace a human" [Interview #13] "What am I worried about? Mainly the shutting down of brains; we rely more and more on these tools without asking ourselves questions about the results they give us" [Interview #22] "The risk is to think that AI is the substitute for complex thinking, in other words, that is a big risk in the sense: leaning on the mere final data of an AI analysis. But if you only look at the final data that the algorithm returned to you, you run the risk of not understanding the complexity of human reasoning and human effort that went into achieving that simplicity of management. It is absurd to think that AI means turning off the brain" [Interview #26]

Source: Authors' own work

multiple relationships, and there is no obviously correct choice or established procedure. Based on that, the interviewees agree that AI can make the final decision, provide the decision maker with possible alternatives and provide simple support to the decision maker. This leads to three main decision-making (Table 7): *automated decisions:* AI has the agency to make decisions autonomously and humans can benefit from AI decision-making scalability, speed and consistency (e.g. automated planning and scheduling); *augmented*

Table 7 Decision-making and AI role

Decision	*AI role*	*Quotes*
Automated	Making the decision	"AI has transformed our operations by automating routine decisions" [Interview #12] "AI can take decisions for specific processes when I have verified that – over time – the decisions it suggested were always successful" [Interview #31] "For example, when AI decides based on a set of data at its disposal, it does not transform that data into knowledge; it just decides. The hope is that the decisions taken are the right ones!" [Interview #33] "I think AI . . . needs to be automated in some sense; in the sense of a system that told me: you're on status A, to go to status B, here's the email" [Interview #30] "We use these tools for their predictive capacity, to make different types of decisions, . . . in most cases operational" [Interview #47]
Augmented	Recommending one or multiple alternatives	"In our organisation, AI doesn't replace human judgment; it amplifies it. They work together to make more informed decisions" [Interview #11] "What AI can do for us is simplify reality, providing us with a number of possible solutions to choose from" [Interview #15] "AI provides us with additional insights and perspectives. This allows us to make more holistic decisions considering various factors." [Interview #17] "With AI augmentation, we can analyse complex datasets and uncover patterns that may not be apparent to human decision-makers. This has enabled us to make more accurate and impactful decisions" [Interview #18]
Supported	Providing insights	"I am firmly convinced that the final decision is up to me, especially when it concerns delicate strategic choices and/or large investments of money. It goes without saying that AI tools can help me, but they can never replace me" [Interview #17] "Through the use of AI-powered analytics, we're able to access real-time data and receive recommendations that support our decision-making. This has enabled us to make more strategic decisions aligned with our business objectives." [Interview #20] "AI provides valuable support in decision-making processes, enhancing our ability to make informed decisions based on data-driven insights." [Interview #25] "Decisions – when they refer to an extremely delicate business process – must always be taken by a human that AI can support" [Interview #31]

Source: Authors' own work

decisions: AI recommends one or multiple alternatives, reducing complexity; thus, humans can rapidly analyse and make decisions (e.g. simulations); *supported decisions:* AI provides valuable insights but are humans – through their common sense, judgement and expertise – that identify the best decision (e.g. hiring processes). The latter circumstance is particularly true when referring to decisions of a strategic nature that – according to interviewees – must always be made by humans, with AI just supporting them.

Thus, the increasing use of AI within KM processes leads to a redefinition of decision-making dynamics within organisations, which entails redefining the relationship between human agency and AI agency. In this vein, it clearly emerges from the interviews that – even though both humans and AI can make decisions independently – the best results come out when they collaborate, i.e. when humans and AI interact and co-create the final decision, allowing organisations to reach their goals:

> It is the intersection between the two [man and AI] that creates the real added value for the organisation. If both are left free to express their full potential, this allows us to co-create the "perfect" experience for our customers [Interview #24].

> Yes, the best decisions are those based on AI and humanity, but their relationship is not fifty-fifty. I mean, although autonomous AI makes many decisions, we keep the decision of what decisions to offload and what to maintain [Interview #33].

> Sometimes decisions are made by AI, sometimes by humans; it is not easy to find the balance, but it is necessary [Interview #48].

5. Discussion

Findings from the interviews have been used to develop an integrated framework synthesising the results obtained through this investigation (Figure 2). The model relates the three investigated concepts, i.e. AI, KM processes and decision-making, highlighting how there is not only a linear relationship between them but also a retroactive one, as graphically shown in Figure 2 and emphasised by many interviewees:

> It's not just about the [AI] tools themselves. It is about understanding how they shape decision outcomes and how those outcomes, in turn, inform our future choices regarding AI [Interview #26].

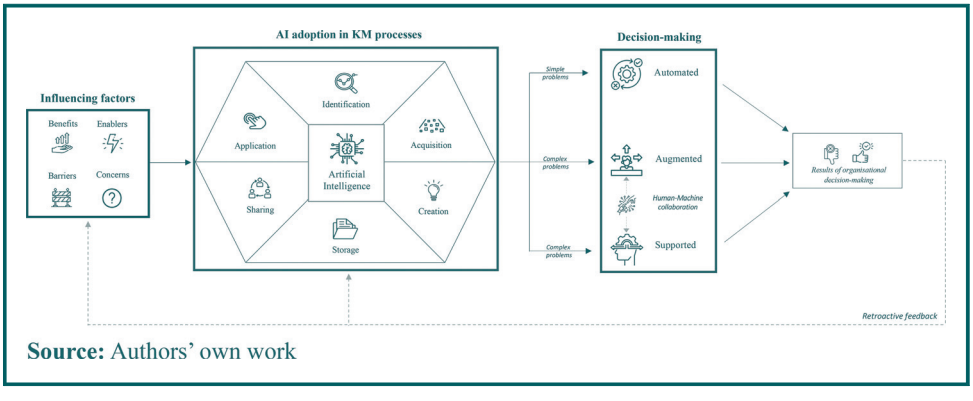
> It's a loop: our results inform our future choices that will influence our future results, and so on [Interview #38].

> AI tools are adopted and improve KM processes, which has a positive impact on the decisions we make. At the same time, the success – or failure – of the results achieved through those decisions will influence how we perceive AI in terms of benefits or problems related to its use. This, in turn, will impact whether and how we re-adopt AI within our KM processes and, therefore, ultimately influence our decisions. This mechanism repeats itself infinitely, self-generating and self-influencing. [Interview #42]

According to Figure 2, there is a *linear* relationship between the different elements that compose the framework: based on the perceived benefits, but also of the identified barriers and all the other influencing factors, the organisation chooses its AI tool(s) and within which KMP adopt it; this generates an ad hoc decision, according to the complexity of the problems that need to be solved, which will lead to specific results (positive/negative). At the same time, the obtained results will influence all the other elements of the framework thanks to the existence of *retroactive* feedback: based on the results derived from the decisions made, the perceived influencing factors change, as well as the choices made regarding the AI adopted and the related KMP. The relationship between AI, KM processes and decision-making underscores the importance of successful AI integration in KM processes, as it directly influences decision results as well as the need to carefully evaluate AI's effectiveness in achieving desired outcomes, as perceptions of its benefits or drawbacks can shape future adoption decisions.

In other words, the provided framework shows that AI, KM and decision-making are interconnected and mutually influence each other, in line with previous contributions that look at organisations as complex systems (Holland, 2006; McElroy, 2000), in which decisions are formed based on the interactions among multiple factors and actors

Figure 2 Decision-making from AI-empowered KM processes



Source: Authors' own work

(Cristofaro *et al.*, 2021; Parasuraman *et al.*, 2000). In this specific case, these interactions are made even more complex by the human–AI interplay (Di Vaio *et al.*, 2022). In this vein, the framework suggests that AI mainly play a complementary rather than competing role with humans (Budhwar *et al.*, 2022), identifying three specific decision-making typologies (i.e. automated, augmented, supported) according to the problem that needs to be solved and the related complexity.

Moreover, the proposed framework includes a feedback loop that helps the organisation learn and improve its knowledge base over time (Argyris, 1990; Argyris and Schön, 1997). In fact, the outcomes of decisions are fed back into the system as "additional knowledge", allowing the organisation to store explicit knowledge from decision-makers and make it immediately available within the overall system (Nemati *et al.*, 2002).

In sum, decision outcomes not only influence future AI adoption and KMP but also reshape the organisation's perceptions of AI benefits and challenges. Moreover, as decisions inform future choices and outcomes, organisations accumulate knowledge and refine their approaches to AI adoption and decision-making. This dynamic interplay suggests a more nuanced understanding of how the investigated elements interact over time, ameliorating organisational agility and responsiveness to changing environments.

5.2 Theoretical implications

The results of this study expand the literature that links AI and KM (Liebowitz, 2001; Sanzogni *et al.*, 2017; Kinkel *et al.*, 2022) by providing empirical – and not just potential (Alavi *et al.*, 2024; Jarrahi *et al.*, 2023) – evidence of its adoption by organisations and of the underlying motivations – in terms of benefits, enablers, obstacles and concerns – which lead knowledge workers to increase their awareness of integrating AI tools into their daily practices and decision-making processes (Kudyba *et al.*, 2020).

The relationship identified between AI adoption, KM processes and decision-making emphasises the interdependence between these topics, highlighting their iterative nature and enriching current theoretical discussions on them (Cao *et al.*, 2021; Duan *et al.*, 2019; Dwivedi *et al.*, 2021). In particular, findings support recent studies that stress the importance of establishing a clear human–AI agency relationship (Chin *et al.*, 2024; Kang and Lou, 2022; Sundar, 2020), as strongly advocated by Budhwar *et al.* (2022), to promote fruitful human–machine collaborations to get the best from both when acting synergistically (Jarrahi *et al.*, 2023; Xiong *et al.*, 2022; Wilson and Daugherty, 2018), especially in terms of decision-making (Bader and Kaiser, 2019; Metcalf *et al.*, 2019). At the same time, our results mirror those of Bigman and Gray (2018) and Haesevoets *et al.* (2021), revealing that people are more willing to accept AI involvement in managerial decisions only if machines play a supportive role.

Moreover, the provided results also contribute to the human resource management literature (Malik *et al.*, 2023b) by providing empirical evidence on how AI adoption is transforming the nature of work, workers and the workplace, highlighting both positive (e.g. ameliorating employees' evaluation/training/learning) and negative (e.g. unskilled human resources) aspects.

Furthermore, findings support recent studies (Caputo *et al.*, 2023; Paniccia *et al.*, 2024) that stress the importance of considering the time variable as well as the capacity of the organisation to make proper estimations in terms of time needed for the AI implementation. In this vein, AI adoption allows organisations to perform specific tasks of KM processes in real time, enabling more informed and timely decisions (Tien, 2017).

Finally, we corroborate and advance previous studies that attempted to identify the factors influencing the adoption of AI (Cho *et al.*, 2023; Kinkel *et al.*, 2022) by providing a list of 20 influencing factors (benefits, enablers, barriers and concerns) of the AI adoption in KM

processes, offering a more comprehensive understanding of the complex dynamics surrounding such adoption.

5.3 Managerial implications

Managers can view the provided model as a guide to verify how their organisation performs in decision-making through AI adoption within KM processes. In this vein, the relationship among investigated topics stresses the importance of adopting a holistic approach. Accordingly, we propose a revisited version of the six steps of the rational decision-making model (Schoenfeld, 2010) to allow managers to fully grasp and exploit the interconnectedness between AI, KM processes and decision-making by providing structured guidelines on how AI can effectively support the decision-making process by enhancing KM practices:

- *Identifying the problem(s) to solve with AI.* Before implementing AI, organisations need to clearly understand what problem(s) they would like to solve through its adoption. This may involve identifying specific knowledge gaps or inefficiencies that AI can address. Valuable questions in this first phase include: *Why do we want to adopt an AI tool? What problem do we solve by using it? Is the problem a simple or a complex one?*
- *Generating and evaluating alternatives.* In this second phase, the organisation is called to create a four-quadrant matrix in which benefits, enablers, barriers and concerns concerning AI adoption are listed clearly and exhaustively. This will facilitate the evaluation of the most suitable AI tool(s) among the many alternatives and, according to the problem typology previously identified, be capable of enhancing KM processes and improving knowledge flow within the organisation. In this vein, organisations have to recognise that the use of technology across the organisation varies considerably according to the tasks different knowledge workers perform (Davenport, 2011). Moreover, integrating AI into KM processes necessitates precise governance mechanisms to ensure the ethical and responsible use of AI technologies (Chin *et al.*, 2024). This may involve establishing AI supervision committees and implementing robust data governance frameworks. In addition, organisations should focus on talent management initiatives to cultivate a new knowledge-based workforce (Kudyba *et al.*, 2020) equipped with the necessary skills to leverage AI tools effectively (Kudyba and Cruz, 2023). This may entail reskilling and upskilling programmes to enhance digital literacy and promote a culture of continuous learning. Valuable questions in this phase include: *Are data (in terms of sources, quality, and quantity) available? Do we have sufficient financial resources? Are employees skilled for this/these specific tool/s? Have we established clear protocols (for example, to handle ethical or regulatory concerns) for adapting the AI tools as needed over time?*
- *Choosing an AI tool.* According to Steps 1 and 2, it will be possible to select the "best" AI tool(s) for the organisation's KM processes' goals. In this phase, the initially identified problems need to be more detailed, explicitly considering the KM processes in which the organisation intends to introduce AI and the type of problem the organisation is addressing. Strategic imperatives stemming from this understanding include prioritising resource allocation towards AI capabilities that enhance decision-making effectiveness and KM efficiency. This may involve investing in AI technologies that support data integration, analytics and natural language processing to facilitate KM processes and decision support. Helpful questions include: *What specific KM goals do I want to achieve? Can the identified AI tool(s) be adopted in multiple KM processes? If yes, how?*
- *Implementing AI tool(s).* Once the best AI tool(s) is identified, setting up a pilot project to try the tool(s) on a small scale before making more significant investments is useful. Once trained, the AI tools can be put in place without forgetting that they require constant monitoring because "everything changes over time" (e.g. business

requirements, technology capabilities, data). Moreover, many AI tools can self-learn, which may require several modifications/adaptations at both organisational and operational levels. In this vein, the interconnectedness between AI, KM processes and decision-making suggests a need for flexible and adaptive organisational structures and processes. Traditional hierarchical structures may inhibit the flow of knowledge and impede decision-making agility. Instead, organisations may benefit from flatter structures that promote cross-functional collaboration and knowledge sharing. Valuable questions in this phase include: *How often and in what ways (i.e. identify specific metrics or KPIs) do we monitor AI tools' effectiveness and efficiency post-implementation? What are processes in place to detect and respond to issues or anomalies in AI tool outputs? How will implementing AI tools impact our existing KM processes and infrastructure?*

- *Evaluating decision effectiveness.* In this phase, the decisions taken are assessed to understand if they could solve the identified problem(s) as expected. The results of this evaluation will have repercussions on all the previous steps, modifying them if necessary. Organisations should adopt a strategic approach aligning with their AI adoption roadmap and organisational objectives. This may involve balancing investments in foundational AI infrastructure with targeted solutions that address specific KM and decision-making challenges. Valuable questions in this phase include: *Was the decision correct/helpful in solving the identified problem? What worked well/poorly and why? Was the problem clearly defined? How did the use of AI impact our KM processes and decision-making outcomes? What lessons can be learned to improve future KM practices and AI integration?*

6. Conclusions

This study simultaneously addresses AI, KM processes and decision-making to provide an original model of the relationships among them, allowing organisations to understand better how to ameliorate their decision-making through AI adoption within KM processes.

Despite theoretical advancements and practical implications provided by the investigation, it is also possible to derive some *limitations* of this work, which also opens the doors to future studies. The interviewees were chosen for reasons of appropriateness rather than representativeness. However, the variety of investigated realities made it reasonable to believe that they are a representative sample of companies of our time, making findings sufficiently generalisable. By using structured case studies or ethnographic research, future studies could offer deeper insights into the nuanced dynamics of AI integration in KM processes and decision-making within specific organisational contexts. Moreover, as most organisations analysed are private, future studies could verify the model's validity by exclusively focusing on the public sector. In addition, longitudinal studies could investigate the long-term impact of AI adoption within KM processes on organisational performance and decision outcomes. Furthermore, comparative studies across different industries and regions could provide valuable insights into the contextual factors influencing AI adoption and its implications for decision-making. Another limitation lies in the qualitative nature of our research. Although the chosen interviewees provided valuable insights, their selection prioritised appropriateness over statistical representativeness. Future studies could address this limitation by employing quantitative methods. In this vein, a survey-based approach could be implemented to measure the broader impact of AI on KM processes and decision-making across a larger, more representative sample.

In addition, the framework identifies three decision-making typologies (automated, augmented, supported) based on the problem complexity and the role of AI. In this vein, future research must delve deeper into understanding how the human–AI interplay influences decision outcomes. Understanding these nuances is essential for designing effective decision support systems and optimising human–AI collaboration (Di Vaio *et al.*, 2022).

Finally, due to the complexity of the phenomena under investigation, we call for future research to adopt a collaborative and interdisciplinary perspective to understand better how people (within and outside organisations) can use and should be educated in using AI tools. In this vein, quantitative analyses could be instrumental.

To conclude, adopting AI is crucial for KM processes within organisations and can help improve their decision-making. At the same time, the phenomenon deserves further investigation, and researchers and practitioners are called to "keep their guard up" in the face of excessive enthusiasm and optimism in adopting AI-related practices.

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