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MATURITY AND READINESS MODELS FOR RESPONSIBLE ARTIFICIAL INTELLIGENCE (RAI): A SYSTEMATIC LITERATURE REVIEW

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Abstract

Artificial intelligence (AI) development and deployment in organizations is of growing interest to the Information systems (IS) discipline. This can be approached from a sociotechnical perspective contributing to managing the unintended outcomes of AI while extending AI use boundaries. This paper presents the findings from a systematic literature review on organizational maturity and readiness for AI development and development. A key finding from this review is that extant research does not sufficiently cover AI systems' humanistic and ethical aspects. This is a hurdle because these aspects are fundamental for the responsible development and deployment of AI ensuring long-term benefits. Drawing from the literature review findings, we provide a matrix for AI maturity from a sociotechnical perspective and a conceptual maturity model with two main dimensions (covering both instrumental AI capabilities and capabilities for responsible AI), twelve conditions and thirty factors.

Keywords: Artificial Intelligence, Maturity Model, Sociotechnical, Responsible, Instrumental

1 Introduction

Technological advancements in Artificial Intelligence (AI) and the ever-increasing data generation bring many benefits to public and private organizations for instance, in transportation, healthcare, finance, and education (Benbya et al., 2021; Berente et al., 2021; Meadows et al., 2022). In 2021, 87% of technology and service providers aimed to adopt AI technologies, and 33% of them stated they would spend $1 million or more on these technologies in the following two years (Meghan Rimol, 2021). As AI becomes widespread and influences people's lives and organizations' operations, the complex sociotechnical aspects of this new ubiquitous technology must be understood and addressed (Benbya et al., 2021; Berente et al., 2021; Dwivedi et al., 2021). The unintentional consequences of AI brought attention to AI-related ethical issues and social challenges (Floridi et al., 2018; Mikalef et al., 2022). Ensuring sustainability for our societies (Pappas et al., 2018) requires using AI responsibly, considering the possible adverse outcomes of AI use (Dignum, 2019; Duan et al., 2019; Vassilakopoulou, 2020). There is a growing body of research on principles (such as fairness, transparency, and accountability) and frameworks for the responsible AI (RAI) (Dignum, 2019; Osoba & Welser, 2017; Kempton & Vassilakopoulou, 2021). Also, sets of RAI principles and metrics have been proposed by high-tech organizations such as Google, Microsoft, and IBM (Google, 2022; IBM, 2021; Microsoft, 2022). As the importance of RAI becomes apparent, and as writings on RAI accumulate, it becomes essential to review and synthesize the growing body of literature, providing a basis for researchers and practitioners.

Researchers have developed Maturity Models (MMs) and Readiness Frameworks for organizations' AI capabilities, relating them to overall digitalization processes (Sadiq et al., 2021). Such models and frameworks can be used as strategic management tools for road mapping and the appropriation of new technologies like AI (Saari & Kuusisto, 2019; Sadiq et al., 2021). They can help organizations enhance their maturity for RAI deployment, taking into account ethical aspects (Fukas et al., 2021;

Yablonsky, 2021). There are two challenges in developing models for RAI maturity. First, researchers tend to focus on technical and business aspects, covering only at a high level the humanistic aspects of AI (Yablonsky, 2021). In this paper, to ensure a good balance, the humanistic aspects that are specific to ensuring responsible AI use are grouped separately from the instrumental ones that relate to technical efficiency and application effectiveness. The second challenge is that a significant part of prior literature on RAI tends to be abstract, which makes it challenging to develop actionable RAI guidelines (Fukas et al., 2021).

Beyond RAI, discussions on Ethical AI are also prevalent in the literature. Ethics refer to systems of accepted beliefs that have been established to control behaviors within specific communities, for instance, professions (e.g. ethics of nursing) or societies (e.g. ethics in Scandinavia). Ethics tend to be situated. In this research, we use the more general term "responsible AI" to capture diverse sets of requirements. Our study aims to provide an overview of extant research on maturity and readiness models for RAI and to provide a comprehensive model leveraging this prior research. The two overarching research questions that we aim to answer are: a) What are the key factors included in prior research on maturity and readiness models for RAI? b) How can we integrate instrumental AI capabilities and capabilities to ensure the responsible use of AI in a comprehensive model?

To answer these questions, we conducted a systematic literature review and leveraged the findings to conceptualize a comprehensive model. Our proposed conceptual model has two axes (responsible and instrumental) (Sarker et al., 2019). Both axes are essential and can limit or reinforce each other throughout an AI system lifecycle. This paper synthesizes the literature and identifies gaps contributing to theorizing RAI maturity and readiness and also proposes a comprehensive model that can be used by practitioners and researchers for further research in the domain.

In the remaining sections, we present related literature on AI maturity models and readiness and also on responsible AI principles. We then elucidate the research method. After this, we present the results. Finally, we discuss the results providing an integrative view and conclude by pointing to the limitations of this research and further research directions.

2 Related Literature

2.1 AI Maturity Models and Readiness

A maturity model is a structured mechanism used as a scale for assessing the current effectiveness of capabilities and ongoing progress in a particular domain (Becker et al., 2009). Capabilities and factors are described in levels or stages of maturity for delivering the services, so capabilities or process performance at the lower locations form a strong foundation for an organization to progress to the upper levels. There are two approaches to constructing maturity models. When using a top-down approach (Becker et al., 2009), a fixed number of maturity stages or levels are established, and then conditions and criteria are created to construct the model. With a bottom-up approach (Lehmkuhl et al., 2013). The first step is to categorize distinct features or factors in capabilities. The bottom-up approach is more common in well-established domains (De Bruin et al., 2005). In this approach, the maturity levels are defined in a second step (Lasrado et al., 2015). Beyond maturity models, readiness models and frameworks have been suggested in Information Systems (IS) research as essential tools for assessing the organizational state of preparation for successful technology adoption (Molla & Licker, 2005). In general, AI maturity models and readiness frameworks include characteristics and guidelines to enable organizations to adopt AI systems successfully (Becker et al., 2009).

2.2 Responsible AI principles

AI's growth and advancement bring many advantages in all domains of human life. However, it is essential not to overlook negative consequences or risks for organizations, employees, and even societies (Berente et al., 2021). For instance, deepfake technology and a chatbot that starts articulating messages beyond the intentions of their creators are famous examples of the irresponsible use of the AI (Libby, 2019; Neff & Nagy, 2016). High-risk AI applications have caused policymakers, researchers, and industry leaders' attention to responsibly developing and deploying AI (Dignum, 2019). As a result, different ethical principles and frameworks (European Commission, 2019; IAPP, 2018; The Public Voice., 2018; UNESCO, 2017) have been proposed to ensure that the use of AI is compatible with regulations and social norms, user anticipations and organizational values. Microsoft is an excellent example at the industry level as a high-tech mega-company. Microsoft proposes six principles (fairness, accountability, transparency, privacy & security, reliability and safety, and inclusiveness) to develop and deploy AI systems. There are also more examples of responsible AI principles from the industry (Coates & Martin, 2019; Wang et al., 2020).

AI is not an easy-to-use or easy-to-deploy technology compared to other digital technologies. Before implementation and during operation, technical and humanistic challenges arise, and organizations must be ready against them by fostering AI maturity and readiness (Jöhnk et al., 2021; Lokuge et al., 2019). Maturity and readiness assessment tools enable organizations to proactively identify the gaps in their AI capabilities (Alshawi, 2007; Molla et al., 2009). However, peer-reviewed papers on responsible AI maturity and readiness are few (Alsheibani et al., 2019; Pumplun et al., 2020). This paper contributes to filling this gap.

3 Method

3.1 Systematic Literature Review

A systematic literature review (SLR) examines a formulated question using systematic and explicit methods to identify, select, and critically appraise relevant research and collect and analyze data from the studies included in the review. SLRs follow a clearly defined protocol or plan where the criteria are defined before the review. In our case, we performed an SLR following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach. The PRISMA checklist, including the 27 items and four-phase flow diagram, was selected to report the current review transparently.

3.2 Search and Selection of Literature

The literature search was performed with the aim of ensuring comprehensive coverage of the literature. The search was confined to the last 15 years (from 2007 to 2022) and to English-written documents. As some terms can be used interchangeably, we included both “artificial intelligence” and “machine learning”. Also, we did not only search using the term “responsible”, but also the terms "ethical" and "accountable" were used as qualifiers for artificial intelligence. Similarly, beyond the term "maturity model", the terms “capability model” and “readiness” were also used. The search was performed within the title, abstract, and keywords of papers using Boolean operators "OR" and "AND" in three major academic databases: Scopus, Web of Science, and the AIS eLibrary. Table 1 provides an overview.

The software Mendeley was used to collect all articles, categorize them based on their provenance (Scopus, Web of Science, AIS eLibrary), remove duplicates and annotate the corpus of identified literature. The following inclusion criteria were defined: 1- Be published in a journal or conference (book, book chapter, etc. were excluded). 2- Include a conceptualization or a practical measurement of AI systems' maturity and readiness. 3- Point out principles or related considerations for the responsible use of AI. 4- Include research motivations that cover both social and technical factors of AI.

Keywords used for the SLR
("artificial intelligence" OR “machine learning") AND ("maturity model" OR "capability model" OR "readiness")
("responsible artificial intelligence" OR "responsible machine learning") AND ("maturity model" OR "capability model" OR " readiness "),
("ethical artificial intelligence" OR "ethical machine learning") AND ("maturity model" OR "capability model" OR " readiness "),
("responsible artificial intelligence principles" OR "responsible machine learning principles ") AND ("maturity model" OR "capability model" OR " readiness "),
("accountable artificial intelligence" OR "accountable machine learning") AND ("maturity model" OR "capability model" OR " readiness ")

Table 1. Keywords used in the search string

We selected papers in three steps; first, we screened all fetched articles' titles to evaluate eligibility based on the inclusion criteria. Then, the abstracts of the remaining publications were screened and checked. In the final step, we carefully reviewed the full text of all remaining papers to identify the included articles. Throughout the three steps of paper selection, the inclusion criteria were applied. Finally, we performed a backward and forward search using the papers that have been singled out as a starting point after checking the full text. This yielded four additional papers that were included in the corpus of literature. Figure 1 presents the flowchart for the paper selection.

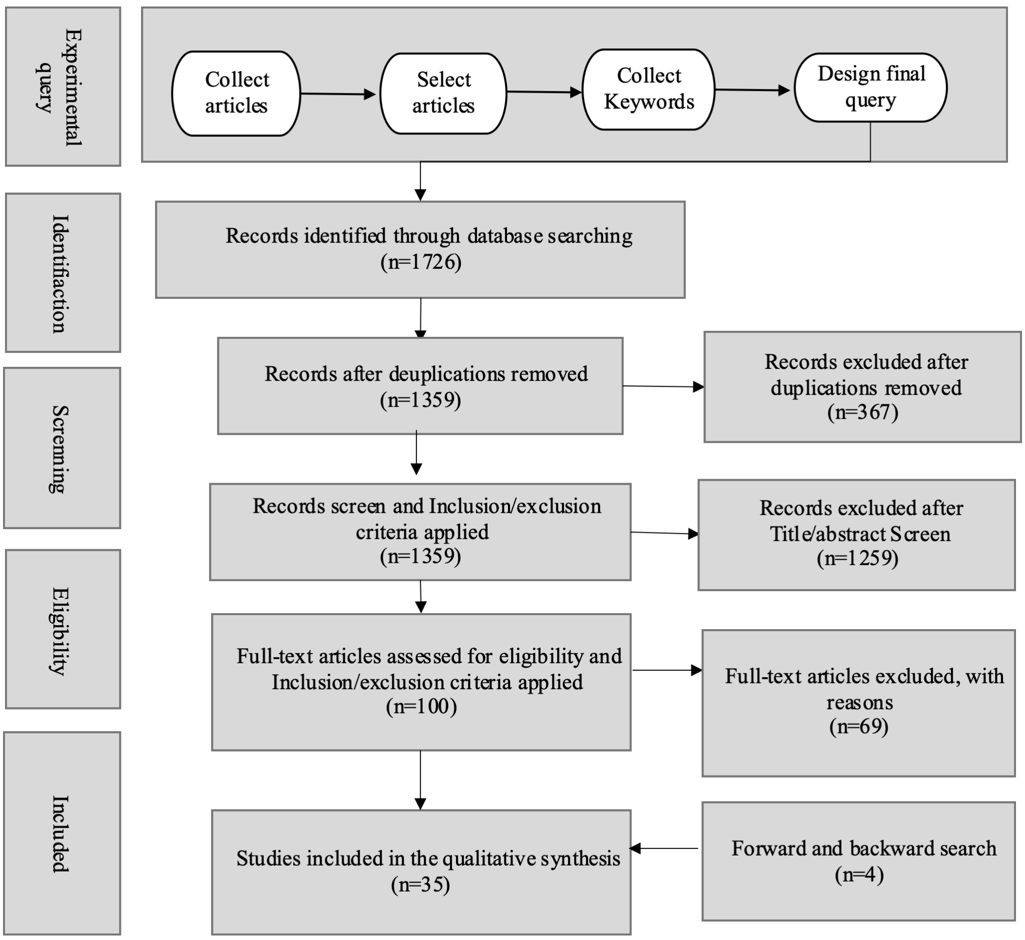

Fig. 1. Flowchart of the search and selection process

3.3 Literature Analysis

During the analysis, critical attributes of all selected papers were noted (for instance, publication date, journal, or conference name). Also, after going through the full text of the papers, they were coded, extracting from the text maturity or readiness dimensions and factors, conceptual and operational models, key results, and conclusions. This coding was used for content analysis. As a first step, the content analysis was performed with the objective of developing a good overview of the included papers. As a second step, we analyzed the content to identify dimensions that are specific to ensuring responsible AI use, grouping them separately from the instrumental ones that relate to technical efficiency and application effectiveness. This distinction is motivated by the work of Sarker and colleagues, who classified sociotechnical systems' technological and social outcomes by distinguishing between instrumental and humanistic objectives (Sarker et al., 2019). In this paper, the humanistic aspects are linked to ensuring responsible AI use and the issues related to the efficiency and effectiveness of AI are classified as instrumental.

4 Results

4.1 Distribution over time, study type and field

The majority of papers (30 out of 35) were published in the last four years (from 2019), indicating this research field's growth. Table 2 provides an overview of the study types. Seven papers are only conceptual, among the remaining ones, mixed method approaches are the most frequent (7 papers).

		Responsible Dimensions Only	Instrumental Dimensions Only	Both Dimensions
Study type	Conceptual	1	6	0
	Mixed method	2	5	0
	Delphi or focus group study	1	4	1
	Survey	1	3	1
	Case-study	1	3	0
	Review	0	2	2
	Content Analysis	0	2	0

Table 2. Study types of included articles (n=35)

In Table 3, the distribution of the selected articles across study fields is presented. The most prevalent fields are: “Business and Operation Research" and "Strategy, Management, Governance".

		Responsible Dimensions Only	Instrumental Dimensions Only	Both Dimensions
Study Field	Business and Operation Research	2	5	1
	Strategy, Management, Governance	2	4	1
	Digital Transformation	0	4	0
	Data Science	0	4	0
	IT and computing systems	1	2	1
	Supply Chain	0	3	0
	Auditing	1	1	1
	Human Resources Management	0	2	0

Table 3. Study fields for included articles (n=35).

4.2 A sociotechnical perspective on AI maturity and readiness models

This systematic literature adopts a sociotechnical perspective (Beath et al., 2013) to explore how technically-oriented (instrumental) and socially-oriented dimensions (related to the responsible use of AI) get interwoven in RAI maturity models. We classified the papers reviewed into four categories by positioning them along these two types of dimensions. In Figure 2 we provide a graphical representation of this categorization.

4.2.1 The technical imperative

The first type of research shows limited or only indirect concern for aspects beyond the technical ones. This means that the researchers focus on technical requirements for improving AI maturity (for example, technical requirements of cyber security).

4.2.2 The social imperative

The second type of research has characteristics that are opposite to type one. Although this approach has helpful insight into the AI maturity models' social components, the technical capabilities affecting the organization's maturity are less noticed. Maturity models in these studies focus on social factors orienting attention to the prevention of unintended consequences of AI. While this is a noble aim, simply focusing on preventing failure can create a governance trap that pays more attention to controls and rules than to making progress.

4.2.3 Sociotechnical interplay

The third type identified covers both technical and social aspects, including their interplay in AI maturity levels. This type is the most compatible with the sociotechnical perspective. Technological and social capabilities interact and coevolve for AI systems that achieve instrumental and responsible outcomes. Within this category, Jöhnk and colleagues and Kinkel and colleagues (Jöhnk et al., 2021; Kinkel et al., 2022) consider AI ethics and awareness as well as IT infrastructure.

4.2.4 The social and technical primitive

The fourth type of research identified examines both social and technical aspects in a limited way. Within this category, Lichtenthalz and Mukherjee & Chittipaka mention technology and social capabilities such as strategic business alignment at a very high level without elaborating on specific factors or capabilities (Lichtenthaler, 2020; Mukherjee & Chittipaka, 2021). The focus of such research is on describing each level of maturity generally.

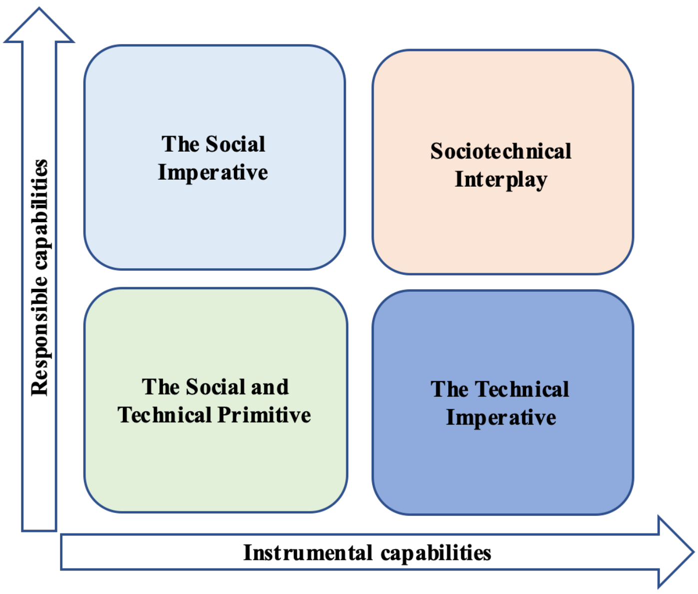

Fig. 2. Classification of the literature in four sociotechnical categories

4.3 Responsible and Instrumental AI factors

In Table 4, the different factors of the responsible dimension and their frequency in the papers reviewed are presented. Fairness, transparency, and ethical awareness are commonly reported. Privacy and lawfulness are also common. Moreover, to examine the applicability of the included articles, we examined if they operationalized the factors included or only included them at a conceptual level. As presented in table 5, the literature shows that most papers are only conceptual. Transparency, fairness and privacy are the factors more frequently operationalized.

Factor	Operationalized	Only Conceptual
Transparency	3	4
Fairness	3	4
Employees ethical awareness	2	5
Privacy	3	3
Human Rights Laws	2	4
Accountability	1	4
Data Governance	1	4
Responsibility	1	3
AI customer empowerment	1	3
Societal Environment well-being	1	2

Table 4. Responsible AI factors in articles reviewed (n=35 – multiple factors appear in each paper).

Table 5 presents the number of papers that address the various factors in the instrumental dimension. The most frequently reported factors are “Technology and IT infrastructure” and “Process & Organization”. Furthermore, similarly to table 4, a distinction is made between articles that only include these factors at a conceptual level and articles that operationalize these factors attempting to develop assessment instruments.

Factor	Operationalized	Only Conceptual
Technology and IT infrastructure	11	18
Process & organization	11	15
Strategic alignment (value-added approach)	9	15
Personnel competences	8	11
Data availability	5	11
Data accessibility	6	9
Data flow	6	8
Top management support	8	8
Organizational Culture	2	6
Financial budget	6	6
Data quality	4	7
Experience with Data-Driven Decision Making	2	4
Culture (e.g. change readiness, innovativeness)	0	3

Table 5. Instrumental AI factors in the articles reviewed (n=35).

Using the literature reviewed, we developed a consolidated list of factors for the responsible and instrumental dimensions. Responsible AI is an emerging topic in the literature, to ensure that this list is as comprehensive as possible, we also went through Responsible AI research papers that were not part of the corpus of literature reviewed as they do not suggest maturity models (Barredo Arrieta et al., 2020; Dafoe et al., 2021; Mayer et al., 2021; Siau & Wang, 2020). These papers were selected because of their focus on Responsible AI. The factors identified were grouped in capabilities (Tables 6 & 7).

Capability	Factor and selected related references	Factor description
Ethical awareness	Customer AI readiness (Jöhnk et al., 2021; Mikalef et al., 2022)	Inform external or internal customers to understand how AI is involved in their experience (fully or partially powered by an AI).
	Employees' ethical awareness (Mikalef et al., 2022; Shneiderman, 2020)	Increase awareness of employees (technical and non-technical staff) through training programs, knowledge sharing, cross-department collaboration.
AI model	Fairness evaluations (Barredo Arrieta et al., 2020; Coates & Martin, 2019; Jantunen, M. et al 2021)	Analysis of the firmness and bias limitations by focusing on the particular decisions (e.g., HR recruitment, medical predations or finance allocations.)
	Explainability and Interpretability (Barredo Arrieta et al., 2020; Coates & Martin, 2019; Fukas et al., 2021)	Explain models to know which of inputs are affecting the output factors and how much they affected.
	Performance of the ML methods (Barredo Arrieta et al., 2020; Chen et al., 2022; Coates & Martin, 2019; Sternkopf & Mueller, 2018)	Using statistical metrics and data mining techniques to evaluate the accuracy of the model.
Cooperative AI	Accountability (Coates & Martin, 2019; Desouza et al., 2021; Mikalef et al., 2022)	Mapping the person or entity responsible for each part of an AI system and to whom they are accountable.
	Transparency (Coates & Martin, 2019)(Chowdhury et al., 2022; Mikalef et al., 2022;)	Formalized procurers to report and explain AI outcomes in precise ways (e.g., visually or in a simple language) to customers.
	Norms and institutions (Chowdhury et al., 2022; Dafoe et al., 2021; Siau & Wang, 2020)	Social tools and infrastructure such as shared beliefs or rules promote understanding, transparency, and accountability.
	Understanding (Dafoe et al., 2021; Jantunen, et al., 2021)	Like an infant, an AI agent must have a basic understanding of its environment and the ability to consider the consequences of actions, predict another's behaviour, and the implications of another's beliefs and preferences.
Data Governance	Data quality (Coates & Martin, 2019; Jöhnk et al., 2021; Martínez-Plumed et al., 2021; Mikalef et al., 2022)	Ensure data quality to omit inaccuracies, errors, mistakes, and socially constructed biases (e.g., the sources of the training data, age of data, data volumes, and the accuracy of data labelling) throughout the entire lifecycle.
	Data Security & Privacy (Chowdhury et al., 2022; Coates & Martin, 2019; Jöhnk et al., 2021; Mikalef et al., 2022)	To ensure safety, record details of actions on privacy-related data (What should be recorded and who should take charge of the recording and accessing data).
Laws & regulations	Organizational authentications (Mikalef et al., 2022)	Particular authorized unit to collaborate and integrate all relevant departments.
	Job automation; (Mikalef et al., 2022; Siau & Wang, 2020)	Protect different stakeholders from unintended consequences of AI automation by laws and regulations?
	Human Rights Laws (Jantunen, M., et al., 2021; Mikalef et al., 2022)	Knowledge of human rights laws in developing AI solutions for decision makers and designers and engineers.
Continuous improvement	Periodical assessments (Coates & Martin, 2019)	Continues measurable system for monitoring the operations.

Table 6. Responsible AI Capabilities and Factors

Capability	Factor and selected related references	Factor description
Technology	Data computation and storage capabilities (Alsheibani et al., 2019; Martínez-Plumed et al., 2021)	to generate, store and compute a large amount of data to handle AI workloads.
	Functional requirements (Alsheibani et al., 2019; artínez-Plumed et al., 2021; Jöhnk et al., 2021)	The functional requirements of AI systems must be defined clearly and aligned to business needs.
	Networking capabilities (Coates & Martin, 2019; Martínez-Plumed et al., 2021)	To transfer, extract and load data quickly and appropriately between systems and machines.
Strategic Alignment	Top management support (Alsheibani et al., 2019; Mukherjee & Chittipaka, 2021; Jöhnk et al., 2021)	Top management support provides wide AI strategies to foster AI commitment, knowledge, and awareness.
	Process & organization (Holmström, 2022; Hradecky et al., 2022; Kinkel et al., 2022)	Reengineering, standardization, and implementation of new processes align with AI strategies.
	Strategic alignment (value-added approach) (Alsheibani et al., 2019; Holmström, 2022; Kinkel et al., 2022)	AI functions require addressing new opportunities or solving an organizational problem to achieve a competitive advantage.
Organizational Culture	Change Management (Chowdhury et al., 2022; Hradecky et al., 2022; Saltz, 2017)	It helps employees to understand and cope with organizational changes.
	Innovativeness (Chowdhury et al., 2022; Desouza et al., 2021; Facchini et al., 2020; Jöhnk et al., 2021)	A culture of innovation is embedded in organizations' DNA, and people do not fear sharing their ideas.
	Collaborative work (Chowdhury et al., 2022; Jöhnk et al., 2021; Saltz, 2017)	Work in teams and combine different skills and perspectives.
Data Management	Data flow (Chowdhury et al., 2022; Fukas et al., 2021; Jöhnk et al., 2021)	Define extract-transfer-load (ETL) processes to establish automated and smooth data streams.
	Data-Driven Decision Making (Alsheibani et al., 2018; Chowdhury et al., 2022; Hradecky et al., 2022; Jöhnk et al., 2021)	Using statistical methods and knowledge acquired by ML models to gain insights into the organization's decision making.
	Data availability (Chowdhury et al., 2022; Facchini et al., 2020; Jöhnk et al., 2021; Sternkopf & Mueller, 2018)	Relevant types and a large amount of data are necessary for AI models to be trained and generate the accurate predictions.
Financial	Financial budget (Chowdhury et al., 2022; Hradecky et al., 2022; Jöhnk et al., 2021)	Allocate financial resources to tailor assets and capabilities to the unique context and their values.
	Cost-benefit analysis (Kinkel et al., 2022; Mukherjee & Chittipaka, 2021)	Compares the AI benefits (or opportunities) with estimated costs to decide whether it makes sense from a business perspective or not
Human resource management	Personnel competences (Chowdhury et al., 2022; Hradecky et al., 2022; Kinkel et al., 2022)	Business analysts and AI experts are appropriate human recourses for improving the maturity of AI in organizations.

Table 7. Instrumental AI Capabilities and Factors.

5 Discussion and Conclusion

5.1 Integrating responsible and instrumental AI capabilities

In this study, we map out the body of literature on maturity models and readiness frameworks for RAI. Adopting a sociotechnical perspective (Mumford, 2006; Sarker et al., 2019), we placed the articles reviewed across two dimensions: one technologically-oriented and one socially-oriented. Furthermore, drawing from the literature we propose a comprehensive model of technical and instrumental AI capabilities. Considering both responsible and instrumental capabilities as essential requirements for implementing AI, the paper contributes an integrative view. Specifically, our study identified 15 factors for responsible AI capabilities and 15 factors for instrumental AI capabilities. The findings of our research are graphically represented in Figure 3. The integrative view proposed allows the development of AI maturity models that conceptualize AI as a socio-technical phenomenon. This conceptualization enables researchers and practitioners to better understand the requirements for AI development and deployment in a responsible way.

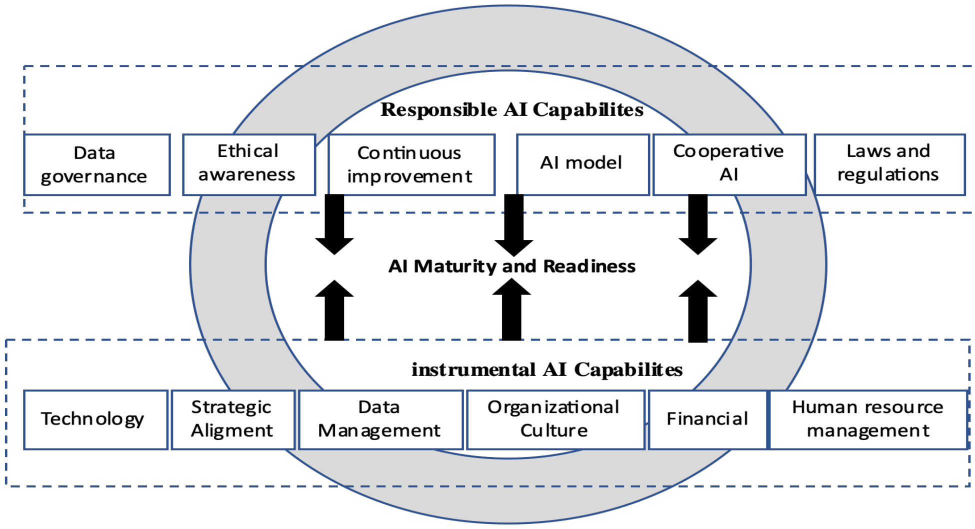

Fig. 3. Integrating responsible and instrumental AI capabilities in maturity models.

5.2 Limitations and future research directions

This systematic study has some limitations, and we would like to acknowledge them. First, the review is limited to the past fifteen years and explicitly focuses on conference and journal papers. Therefore, the study may have overlooked relevant books or articles published before 2007. The use of AI has significantly increased in recent years; however, AI technologies have been discussed in the literature for more than five decades; hence some relevant papers may have been published during the early AI times. Furthermore, our study is based only on literature analysis.

Further research can empirically validate and potentially expand our findings. A mixed-method approach could be beneficial for such further research. Empirical research can also explore the relationship between the factors identified and how they can reinforce or restrict one another. Future research can also investigate the prioritization and weighting of different factors assessing their influence on the success of AI initiatives.

Appendix: Papers Reviewed

No	Authors and Title	Outlet	Year
1	(Alsheibani et al.), Towards an Artificial Intelligence Maturity Model: From Science Fiction to Business Facts	PACIS	2019
2	(Jantunen et al.), Building a Maturity Model for Developing Ethically Aligned AI Systems	IRIS	2021
3	(Fukas et al.), Developing an artificial intelligence maturity model for auditing	ECIS	2021
4	(Schuster et al.), Maturity Models for the Assessment of Artificial Intelligence in Small and Medium-Sized Enterprises	PLAIS EuroSymposium	2021
5	(Russell et al.), Organic Evolution and the Capability Maturity of Business Intelligence	AMCIS	2010
6	(Ojaswini Malhotra, et al.), Cyber Security Maturity Model Capability at The Airports	ACIS	2021
7	(Sternkopf and Mueller), Doing Good with Data: Development of a Maturity Model for Data Literacy in Non-governmental Organizations	HICSS	2018
8	(Komatsu & Mantovani,), Business Intelligence Maturity Level in Brazilian Companies	AMCIS	2021
9	(Saltz), Acceptance factors for using a big data capability and maturity model	ECIS	2017
10	(Felch et al.), Maturity Models in the Age of Industry 4.0 – Do the Available Models Correspond to the Needs of Business Practice?	HICSS	2019
11	(Sadiq et al.), Artificial intelligence maturity model: a systematic literature review	PeerJ Computer Science	2021
12	(Chen et al.), Establishment of a maturity model to assess the development of industrial AI in smart manufacturing	ENTERPRISE INFORMATION MANAGEMENT	2022
13	(Hujran et al.), Digitally Transforming Electronic Governments into Smart Governments: SMARTGOV, an Extended Maturity Model	Information Development	2021
14	(Baglio et al.), A maturity model to assess the adoption of “Logistics 4.0” technologies in the 3PL industry	Summer School F. Turco - Industrial Systems Engineering	2021
15	(Pappel et al.), Maturity Model for Automatization of Service Provision and Decision-Making Processes in Municipalities	ICICT	2022
16	(Bettoni et al.), An AI adoption model for SMEs: A conceptual framework	INCOM	2021
17	(Vermeulen et al.), Industry 4.0 – Artificial Intelligence (AI) contribution to capability maturity	International Annual Conference of the American Society for Engineering Management	2021
18	(Moonasar and Naicker), Cloud capability maturity model: A study of South African large enterprises	South Africa Journal of Information Management	2020
19	(Barbara Dinter), The Maturing of a Business Intelligence Maturity Model	AMCIS	2022
20	(Desouza et al.), Maturity Model for Cognitive Computing Systems in the Public Sector	HICSS	2021
21	(Facchini et al.), A Maturity Model for Logistics 4.0: An Empirical Analysis and a Roadmap for Future Research	Sustainability	2020
22	(Williams and Lang), Digital Maturity Models for Small and Medium-sized Enterprises: A Systematic Literature Review	ISPIM	2019
23	(Coates and Martin), An instrument to evaluate the maturity of bias governance capability in Artificial Intelligence projects	IBM-Journal of Research and Development	2019

24	(Ellefsen et al.), Striving for excellence in AI implementation: AI maturity model framework and preliminary research results	Scientific Journal of Logistics	2019
25	(Lichtenthaler), Five maturity levels of managing AI: from isolated ignorance to integrated intelligence	Journal of Innovation Management	2020
26	(Jöhnk et al.), Ready or Not, AI Comes— An Interview Study of Organizational AI Readiness Factors	Business and Information systems Engineering	2021
27	(Mikalef et al.), Thinking responsibly about responsible AI and 'the dark side' of AI	European Journal of Information systems	2022
28	(Holmström), From AI to digital transformation: The AI readiness framework	Business Horizons	2022
29	(Chowdhury et al.), Unlocking the value of artificial intelligence in human resource management through AI capability framework	Human Resource Management	2022
30	(Hradecky et al.), Organizational readiness to adopt artificial intelligence in the exhibition sector in Western Europe	International Journal of Information Management	2022
31	(Martínez-Plumed et al.), Futures of artificial intelligence through technology readiness levels	Telematics and Informatics	2021
32	(Alsheibani et al.), Artificial Intelligence Adoption: AI-readiness at Firm-Level	PACIS	2018
33	(Kinkel et al.), Prerequisites for the adoption of AI technologies in manufacturing – Evidence from a worldwide sample of manufacturing companies	Technovation	2022
34	(Pillai & Sivathanu), Adoption of artificial intelligence (AI) for talent acquisition in IT/ITeS organizations	Benchmarking	2020
35	(Mukherjee & Chittipaka,), Analysing the Adoption of Intelligent Agent Technology in Food Supply Chain Management: An Empirical Evidence	FIIB Business Review	2021

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