Dynamic Dialogue for Organizational Knowledge Acquisition: Expert Insights on Agentic AI use for AI Readiness Assessment

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Abstract: Organizations increasingly recognize Artificial Intelligence (AI) as a strategic capability, yet many struggle to assess and understand their true readiness to adopt and scale AI solutions. Existing AI readiness assessments rely mostly on static surveys and internally collected data, which often fail to capture organizational dynamics and cross-functional dependencies. They also impose substantial time demands while delivering limited perceived value to participants, particularly in Small Medium Business (SMB) companies. Consequently, assessment outcomes frequently generate fragmented insights, limiting their usefulness for strategic forecasting and organizational learning. This study builds on conceptual framework proposing multi-agent conversational diagnostic system, which combines dynamic interview dialogues and public data (OSINT) to acquire richer knowledge about AI readiness and generate actionable recommendations for AI implementation. To refine and validate the proposed approach, we conducted 15 semi-structured expert interviews with senior practitioners involved in AI transformation, including CEOs, sales and technical directors. The sample represents a balanced cross-section of large enterprises and SMBs. The interviews explored experts' perceptions of current knowledge management practices in organizational assessments and expectations toward agentic AI systems capable of dynamic dialogue based diagnostics and recommendations. Results indicate expert agreement that static interview and survey approaches inadequately capture contextual organizational knowledge. Experts expressed interest in dynamic dialogue mechanisms that enable clarification and contextual probing to improve knowledge acquisition processes. At the same time, participants highlighted risks associated with agentic AI usage, including concerns regarding diagnostic quality, replicability, transparency and perceived value for participants. Experts further emphasized that integrating internal organizational knowledge with external public data can improve the results. The study contributes to Knowledge Management by reframing AI readiness assessment as a dynamic knowledge acquisition rather than a static task. Using a Design Science Research approach, the proposed agentic AI artefact offers a foundation for developing adaptive diagnostic systems that support strategic decision-making process, enhance organizational learning and improve the actionability of AI readiness assessments.

Keywords: : Agentic AI, Knowledge management, AI readiness, Conversational diagnostics, Multi-agent systems

1. Introduction

Artificial Intelligence (AI) has become a central capability in digital transformation strategies across all industries. Organisations increasingly deploy AI to support decision-making, automate operational processes and generate strategic insights. Despite this growing popularity, many organisations struggle to evaluate their readiness to implement and scale AI technologies effectively. Assessing organisational AI readiness has therefore became an important managerial activity for identifying implementation barriers and guiding strategic investment decisions (AlSheibani, Cheung and Messom, 2018; Jöhnk, Weißert and Wyrtki, 2021; Mikalef and Gupta, 2021).

Most existing AI readiness assessment rely on structured surveys, maturity models and internally collected organisational data. These instruments typically capture information through predefined questionnaires administered across organisational units. While such approaches provide structured measurement frameworks, they often struggle to capture the complexity of organisational knowledge underlying AI adoption. Readiness related knowledge is frequently distributed across organisational roles, embedded in operational practices and shaped by contextual factors that static survey instruments cannot fully represent. Consequently, traditional readiness assessments often produce fragmented insights that fail to reflect the organisational context in which AI technologies are implemented. Surveys capture explicit responses but rarely uncover tacit knowledge, cross-functional dependencies or contextual explanations behind particular practices. Moreover, static surveys require substantial time from participants, while providing limited perceived value, particularly in Small and Medium sized (SMB) organisations where resources for diagnostic initiatives are constrained. This often results in survey fatigue and response quality issues (Ward and Meade, 2023).

Recent advances in AI create opportunities to rethink how organisational diagnostics are conducted. At the same time, the increasing integration of AI into organisational decision-making raises new governance and learning challenges. Recent research highlights the importance of hybrid human–AI collaboration models that combine automated insights with human judgement and organisational learning processes (Dellermann *et al.*, 2019). However, despite growing interest in AI governance and organisational adoption, limited research has examined how conversational AI systems could support organisational diagnostics and readiness assessment.

To address this gap, this study investigates expert perspectives on the use of agentic AI systems for organisational AI readiness assessment. The research builds on a conceptual framework proposing multi-agent conversational diagnostic systems that combine dialogue-based knowledge acquisition with external open-source intelligence (OSINT) data sources (Jonak and Wodecki, 2026). To refine this concept, 15 semi-structured interviews were conducted with senior practitioners involved in AI and digital transformation initiatives, including CEOs, technical directors, sales, marketing directors and project managers from both large enterprises and SMB organisations.

The interviews explored various elements related to AI readiness including:

- expert experiences with current readiness assessment methods and their perceived limitations
- their expectations regarding the design of agentic AI systems capable of conducting dialogue-based organisational diagnostics
- potential risks associated with such systems, including diagnostic transparency, reliability and the need for human-in-the-loop oversight in automated assessment processes.

The study is guided by the following research questions:

RQ1: How do experts evaluate the limitations of survey-based AI readiness assessments?

RQ2: What capabilities should conversational agentic AI systems possess to enable effective organisational diagnostics?

RQ3: What opportunities and risks do experts associate with the use of agentic AI for organisational readiness assessment?

The findings indicate broad expert agreement that traditional survey based diagnostics often fail to capture contextual organisational knowledge required for meaningful AI readiness assessment. At the same time, practitioners expressed strong interest in dynamic dialogue mechanisms capable of clarifying responses, adapting questions and integrating knowledge across organisational domains. However, experts also emphasised the importance of transparency, diagnostic quality and human oversight to ensure trust in AI driven systems.

Building on these insights, the study connects knowledge management theory with AI readiness assessment by proposing conversational agentic AI as a mechanism for dynamic organizational knowledge acquisition.

2. Conceptual Background

Organisational knowledge is commonly treated as a key resource enabling firms to make decisions, innovate and adapt to changing environments. However, what is often overlooked is how difficult it is to actually access and integrate this knowledge in practice. While part of organisational knowledge can be codified and stored, a substantial portion remains embedded in routines, interactions and individual experience (Grant, 1996; Alavi and Leidner, 2001). This creates a fundamental tension between what organisations know and what they are able to formally capture.

Traditional approaches to organisational diagnostics often rely on surveys or structured interviews that attempt to extract information in predefined formats. Such approaches are effective in collecting explicit knowledge about organisational structures, resources or strategies, but they often fail to capture deeper contextual insights regarding how organisational processes actually function in practice. As (Davenport and Prusak, 1998) suggest, effective knowledge acquisition requires mechanisms that allow interpretation, contextualisation and dialogue rather than purely structured data collection. This becomes particularly problematic in the context of AI adoption, where relevant knowledge is distributed across functions and often shaped by team practices rather than formal structures.

2.1 Tacit Knowledge and Dialogue Based Knowledge Elicitation

Capturing tacit organisational knowledge has long been recognised as one of the central challenges in knowledge management. (Polanyi 1966) described tacit knowledge as knowledge that individuals possess but cannot fully articulate. Because tacit knowledge is experiential and context-dependent, it is often difficult to extract through structured questionnaires or static survey instruments.

Knowledge management researchers have therefore emphasised the importance of dialogue-based knowledge elicitation processes. Through dialogue, individuals can explain reasoning, clarify ambiguous statements and provide contextual examples that reveal deeper organisational insights. Nonaka's knowledge creation theory emphasises social interaction and dialogue as mechanisms enabling the conversion of tacit knowledge into more explicit forms of organisational knowledge (Nonaka & Takeuchi, 1995).

In the context of organisational diagnostics, this suggests that static data collection methods may overlook important contextual information. A more interactive approach allows the diagnostic process to follow emerging insights rather than forcing responses into predefined categories.

2.2 Conversational AI and Agentic AI as a Knowledge Collection Tool

Recent advances in conversational AI have created new opportunities to support knowledge acquisition processes. Compared with traditional survey instruments, conversational systems can dynamically adjust questions based on previous responses, request clarification and explore relationships between organisational practices. Research on conversational survey methodologies suggests that interactive dialogue may generate richer and more contextually grounded responses than traditional questionnaires (Xiao *et al.*, 2019).

While conversational AI systems typically operate as reactive dialogue interfaces that respond to user inputs, agentic AI extends this paradigm by introducing autonomous goal-oriented behaviour. Agentic systems are capable of planning, taking actions, coordinating multiple agents and dynamically integrating internal and external data sources. In contrast to traditional conversational systems, which primarily facilitate interaction, agentic AI systems actively manage the diagnostic process, adapt strategies and orchestrate knowledge acquisition tasks across multiple agents.

From a knowledge management perspective, conversational AI systems can therefore function as knowledge elicitation tools that support the capture and integration of distributed organisational knowledge. At the same time, their use in organisational diagnostics introduces new challenges related to transparency, reliability and trust in automated systems.

2.3 Human AI Collaboration in Organisational Decision Processes

The increasing use of AI in organisations has shifted attention from automation toward collaboration. Rather than replacing human decision-making, many AI systems function as support tools that complement human expertise.

Research on hybrid intelligence suggests that decision quality can improve when human expertise and AI generated insights are effectively combined (Dellermann *et al.*, 2019). In such systems, AI can process large volumes of information and identify patterns, while humans contribute contextual understanding, ethical judgement and strategic interpretation. This balance is particularly important in diagnostic contexts. When AI is used to assess organisational capabilities, such as readiness for AI adoption, its outputs should not be treated as definitive conclusions. Instead, they should be seen as inputs into a broader decision-making process that remains anchored in human interpretation.

2.4 Research gap

Despite growing interest in AI adoption and organisational AI readiness, most readiness assessment frameworks rely on static surveys or structured interviews to collect organisational data (Jöhnk, Weißert and Wyrtki, 2021; Mikalef and Gupta, 2021). These approaches treat readiness assessment primarily as a measurement task rather than a process of organisational knowledge acquisition. Advances in conversational AI create opportunities to design diagnostic systems capable of dynamically eliciting organisational knowledge through dialogue. However, limited empirical research has examined how practitioners perceive such systems, what capabilities they should possess and how automated diagnostics should be balanced with human oversight. Addressing these questions is essential for designing AI enabled diagnostic systems that effectively support organisational learning and strategic decision-making.

3. Methodology

3.1 Research Design

The research adopts the Design Science Research (DSR) methodology to design and evaluate a novel diagnostic artefact supporting organizational AI readiness assessment. Design Science Research provides a rigorous framework for addressing complex real-world problems through the creation and evaluation of technological artefacts that simultaneously generate practical utility and theoretical contributions (Hevner *et al.*, 2004; Peffers *et al.*, 2007). DSR is widely applied in information systems and management research when the objective is to build innovative solutions addressing organizational or technological challenges (Hevner *et al.*, 2024). In the context of this research, the artefact is an Agentic AI based diagnostic system designed to assess organizational readiness for artificial intelligence adoption by integrating internal survey responses with external public data sources.

The choice of DSR is particularly appropriate because the research problem combines theoretical and practical dimensions. Organizations require effective diagnostic tools to understand their readiness for AI adoption, while existing readiness assessment frameworks often rely on static survey instruments that fail to capture organizational dynamics and contextual knowledge (Jöhnk, Weißert and Wyrtki, 2021). The DSR methodology enables iterative development of the proposed solution while grounding the artefact design in empirical insights obtained from both literature and expert practitioners.

Following established DSR frameworks, the research process consists of four interrelated phases:

1. Problem identification and requirements definition
2. Artefact design and development
3. Demonstration and evaluation
4. Communication of results and theoretical generalization

This research combines a literature review with expert interviews to identify limitations of current readiness assessment approaches, define functional requirements for the proposed diagnostic system and validate initial framework proposal. These elements are part of the DSR phase 1 and will allow move to the artefact design and development phase.

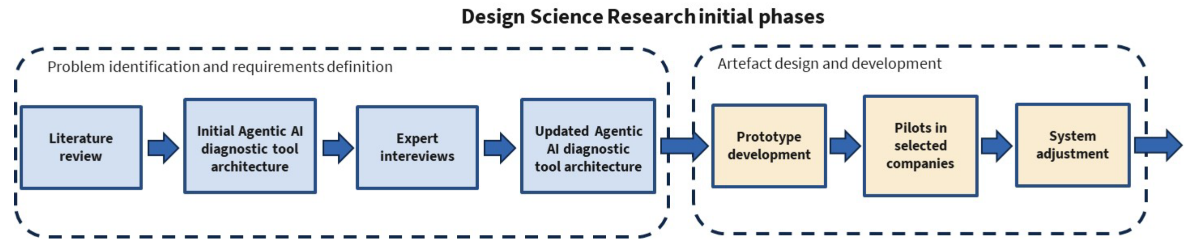

Figure 1: Design Science Research flow

3.2 Expert Interviews

To complement the literature review and capture practical perspectives on organizational readiness assessment, semi-structured expert interviews were conducted with senior professionals involved in technology management and organizational transformation. Expert interviews are especially useful for identifying design requirements for new technological artefacts and for validating conceptual frameworks before system implementation.

Fifteen semi-structured interviews were conducted with senior practitioners across corporate and small to medium size companies (SMBs) operating in Poland. The sample included: CEOs and founders, technical directors, Sales and marketing directors, HR leaders, Development and Project managers. This role diversity allowed the study to capture multiple organisational perspectives on AI readiness. While the majority of firms operated within digitally engaged sectors (IT services, communication, media, logistics, manufacturing), the sample intentionally included both corporate and SMB contexts to increase analytical variation. Interviews followed a semi-structured format, allowing respondents to discuss their experiences with technology adoption, organizational readiness and survey-based assessment methods while also reacting to the proposed concept of an AI-driven diagnostic system. The interviews were conducted face to face (6) or online (9) and recorded with participant consent. All transcripts were anonymized prior to analysis to ensure confidentiality.

3.3 Qualitative Analysis and Coding

Interview transcripts were analysed using thematic qualitative coding, a widely applied method for identifying patterns and themes within qualitative datasets (Braun and Clarke, 2006). The coding process followed an inductive-deductive approach. Initial codes were derived from the conceptual framework of organizational AI readiness identified in the literature (Jöhnk, Weißert and Wyrtki, 2021), while additional themes emerged inductively from the interview data.

A coding scheme was developed to capture recurring themes related to:

- limitations of static survey methodologies
- importance of organizational context in readiness assessments
- role of data, infrastructure and employee competence in AI adoption
- need for personalized and adaptive diagnostic processes
- expert perspectives on the potential and risks of AI-based diagnostic systems.

To enhance analytical rigor, the coding process followed a two-step procedure. In the first stage, initial codes were applied independently to a subset of transcripts and iteratively refined. In the second stage, the full dataset was coded using the final coding scheme. To improve consistency, selected transcripts were re-coded and compared, ensuring alignment in code interpretation.

Multiple themes could be assigned to individual interview segments where relevant. The coding results were then aggregated to identify dominant patterns across the expert sample and to extract representative statements illustrating key findings. This qualitative analysis served two purposes. First, it provided empirical evidence supporting the limitations of traditional survey based readiness assessment approaches. Second, it generated design insights informing the architecture and functionality of the proposed Agentic AI diagnostic artefact.

3.4 Artefact Design and Development

Insights from the expert interviews are used to validate and further develop the proposed Agentic AI diagnostic system. The artefact is implemented as a multi-agent system (MAS), in which multiple specialized agents collaborate to collect, analyse and synthesize information about an organization's AI readiness. The system employs the ReAct reasoning framework, which combines reasoning and action in large language models (Yao *et al.*, 2023). This framework allows agents dynamically adapt questions during the diagnostic interview and integrate information from both internal responses and external public sources.

During interviews the proposed structure of MAS was presented to receive participants feedback, especially about dynamic dialogue process implementation, knowledge acquisition and results presentation. The outcome is adjusted structure of the artefact, which will be then tested with selected companies to gather additional feedback and drive further adjustment to the system. Such approach fits in the DSR process as it support iterative design of the artefact during the research process.

Although a full empirical evaluation of the artefact is planned in the next phase of the research, the current study includes an initial form of design-oriented evaluation through expert validation. The proposed system architecture and interaction logic were presented to participants during interviews, allowing for scenario-based feedback and iterative refinement of design assumptions.

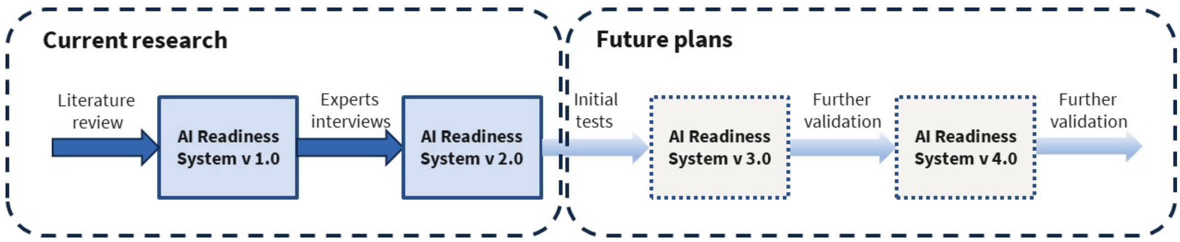

Figure 2: Artefact design and evaluation process

4. Results

The expert interviews provided important insights into how organizations currently evaluate technological readiness and how practitioners perceive the potential role of AI supported diagnostic systems. The qualitative analysis revealed several recurring themes related to the limitations of traditional survey based assessments and the design requirements for a next-generation AI readiness diagnostic system.

4.1 Limitations of Traditional Survey Based Readiness Assessments

A dominant theme across the interviews concerned the limitations of traditional survey based readiness assessments. Experts frequently pointed out that standardized questionnaires often fail to reflect the specific context of an organization and therefore produce limited actionable insights. Several respondents emphasized that generic survey questions rarely capture the complexity of real organizational environments.

For example, a Technical Director explained:

> *"Problem with surveys is when they are not adapted to the recipient… the value of such a survey is simply zero."*

Similarly, a CEO of a media company noted that many organizational surveys fail to generate meaningful insights because they lack contextual depth:

> *"You can answer survey questions very quickly, but they often do not reflect what is really happening inside the company."*

Experts also emphasized that static questionnaires provide no opportunity for clarification or follow-up questions, which often leads to incomplete or superficial responses.

These observations indicate that traditional survey-based approaches may struggle to capture the contextual and dynamic aspects of organizational readiness for AI adoption.

4.2 Need for Contextual and Adaptive Diagnostics

Another strong theme emerging from the interviews concerns the importance of contextual understanding in readiness assessments. Experts repeatedly emphasized that evaluating AI readiness requires a deeper understanding of organizational processes, operational structures and decision-making practices. A Project Manager working in manufacturing explained:

"First you need to understand how the organization works and what its processes look like. Only then you can realistically assess whether automation or AI will bring value."

Similarly, a Development Manager in a technology company highlighted the importance of contextual exploration:

"You cannot evaluate readiness based only on answers to predefined questions. You need to understand the context in which the company operates."

These statements suggest that readiness diagnostics should not rely solely on fixed questionnaires but should include mechanisms enabling contextual exploration and adaptive questioning. Such insights provide empirical support for the concept of conversational diagnostic systems, in which AI agents dynamically adapt questions based on the respondent's previous answers.

4.3 Importance of Organizational Capabilities for AI Readiness

Experts also discussed several organizational capabilities that they consider critical for evaluating readiness for AI adoption. These insights broadly align with dimensions identified in existing AI readiness frameworks (Jöhnk, Weißert and Wyrtki, 2021). Three themes appeared particularly frequently:

- Data and infrastructure readiness

Several experts emphasized that AI adoption requires the presence of digitalized processes and structured data. A CTO from a telecommunications company explained:

> *"Before you even start thinking about AI, you need to ensure that the data is digitalized and accessible."*

Similarly, a Founder of a digital services company noted:

> *"If the organization does not have integrated systems like ERP or structured databases, AI initiatives will struggle to produce meaningful results."*

These insights highlight the continued importance of digital infrastructure and data maturity as foundational elements of AI readiness.

- Employee competence and technological literacy

Another frequently mentioned theme concerned the importance of employee knowledge and technological competence. Experts emphasized that AI tools should be understood as productivity supporting technologies rather than autonomous decision making systems. A VP of Service in an IT services company described this relationship as follows:

> *"I treat AI primarily as a tool that helps employees work more efficiently. But it still requires people who understand how to use it properly."*

Similarly, a Marketing Director explained:

> *"Some employees immediately start experimenting with AI tools, while others avoid them completely."*

These observations suggest that organizational readiness for AI adoption depends not only on technological infrastructure but also on employee competence and learning culture.

- Leadership support and strategic direction

Several respondents also emphasized the importance of leadership support in enabling AI adoption. A Sales Director in a technology company noted:

> *"If management encourages experimentation with new technologies, employees are much more likely to try AI solutions."*

4.4. Integration of internal and external knowledge sources

Another important insight emerging from the interviews concerns the potential value of integrating internal organizational information with external public data. Some respondents suggested that public signals may provide useful indicators of organizational technological maturity. A HR Director pointed out:

> *"You can often learn a lot about a company by looking at the skills they are hiring for or the technologies they mention in job postings."*

Similarly, a CEO from the technology sector suggested that external signals may complement internal assessments:

> *"Public information about technology investments or partnerships can reveal whether a company is actually serious about digital transformation."*

These observations support the concept of incorporating Open Source Intelligence (OSINT) into AI readiness assessments.

4.4 Human Oversight and Trust in AI Diagnostics

While experts generally expressed interest in AI-supported diagnostic systems, they also emphasized the importance of maintaining human oversight. Several respondents expressed concerns regarding the reliability and interpretability of AI-generated assessments. A Technical Director explained:

> *"AI can support analysis, but final decisions should always remain with humans."*

Similarly, a CEO emphasized the importance of managerial responsibility: "Even if AI provides recommendations, someone in the organization must remain responsible for interpreting them."

These perspectives highlight the importance of incorporating human-in-the-loop mechanisms into AI based diagnostic systems.

5. Discussion

The findings of this study provide important insights into the limitations of traditional AI readiness assessment approaches and offer empirical guidance for the development of AI supported diagnostic systems. The results confirm that organizational readiness for AI adoption, especially with rapid technology development, cannot be captured through static survey instruments alone. Instead, readiness assessment should be understood as a dynamic knowledge acquisition process that requires contextual exploration, iterative clarification and integration of multiple knowledge sources. This perspective aligns with broader developments in knowledge management research, which emphasize the importance of interactive knowledge elicitation and contextual understanding when assessing complex organizational capabilities (Nonaka & Takeuchi, 1995; Alavi & Leidner, 2001). AI readiness assessment therefore represents not only a measurement problem but also a process of organizational knowledge discovery.

5.1 Implications for the Design of Agentic AI Diagnostic Systems

The main objective of this study was to evaluate how the proposed Agentic AI diagnostic system, originally introduced in the conceptual framework, should be refined based on expert feedback. The empirical findings from the interviews provides several critical inputs for the design requirements for the proposed Agentic AI diagnostic system. They are presented in below table together with recommendation how they should be incorporated into the architecture of the proposed multi-agent diagnostic system.

Table 2: Design requirements

Design Requirement	Inputs from Expert Interviews	Implication for the Artefact
Adaptive conversational data collection	Traditional surveys fail to capture organizational context and often contain generic questions. Additionally effective diagnostics require the possibility to ask follow-up questions and clarify answers.	Replace static questionnaires with adaptive conversational interviews driven by an AI agent.
Role based diagnostic personalization	Technology readiness differs across organizational functions such as marketing, operations or product development. Static surveys rarely account for these differences.	Adapt questions to the respondent's role and domain expertise using contextual information gathered in the initial interview phase.
Organizational context awareness	AI readiness cannot be evaluated without understanding internal processes, decision structures and operational maturity of the organization.	Collect contextual information during the process and use it to interpret responses and adjust diagnostic paths.
Integration of external organizational signals	Public signals such as hiring trends, technology announcements or strategic communication may provide additional insights.	Integrate Open Source Intelligence (OSINT) sources including company reports, job postings and public technology signals.
Human-in-the-loop validation	Concerns about relying solely on automated AI diagnostics and emphasized the need for human oversight when interpreting results.	Include a human validation step during the diagnostic process to verify results before final recommendations are generated.
Actionable recommendations for organizations	Organizations often participate in surveys without receiving useful insights in return. This reduces engagement and perceived value of assessments.	Generate tailored recommendations and improvement actions based on diagnostic results.

These findings will be incorporated in final design of the IA readiness artefact and then tested with selected companies to validate the AI Readiness system architecture.

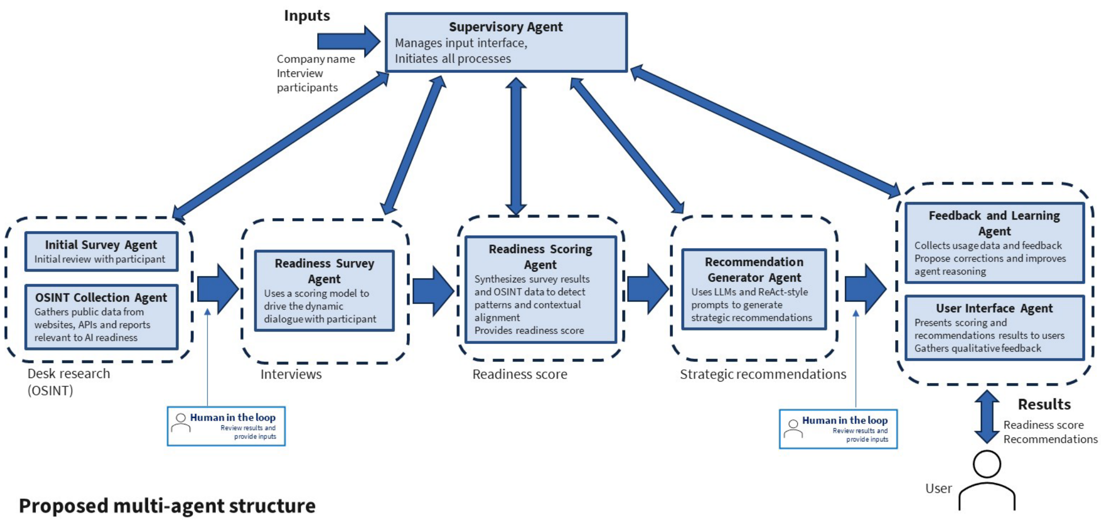

Figure 3: AI Readiness system architecture v. 2.0

5.2 Implications for Knowledge Management and AI Readiness Research

This study positions AI readiness assessment as a structured organizational knowledge acquisition process, involving elicitation, integration and interpretation of distributed knowledge across organization.

Existing readiness frameworks typically rely on structured surveys and predefined maturity models (Jöhnk et al., 2021). While such frameworks provide valuable conceptual guidance, the results of this study suggest that static measurement instruments may be insufficient for capturing the dynamic and context-dependent nature of organizational AI adoption. By reframing readiness assessment as a knowledge acquisition process supported by adaptive AI agents, this research introduces a new perspective on how readiness diagnostics may evolve in increasingly complex technological environments and how it can be adjusted with technology development.

The risks identified by experts, including lack of transparency, diagnostic reliability and trust, highlight the need for structured governance mechanisms in agentic AI systems. These risks may be mitigated through several design principles. First, explainability mechanisms should be incorporated to allow users to trace how conclusions are generated. Second, human-in-the-loop validation should ensure that diagnostic outputs are reviewed and contextualized by domain experts. Third, modular multi-agent architectures may improve transparency by separating data collection, reasoning and recommendation functions. Finally, governance frameworks defining responsibility and accountability are essential to support organizational trust in AI-driven diagnostics.

6. Limitations and Future Research

This study has several limitations that should be considered when interpreting the results. First, the empirical findings are based on expert interviews conducted within a specific organizational and geographical context. Although the experts represented diverse industries and organizational roles, additional studies involving larger and more internationally distributed samples may provide further insights. The Polish context may also influence expert perspectives due to specific characteristics such as varying levels of AI adoption across industries, differences in digital maturity between large enterprises and SMBs, and evolving regulatory and market conditions. These contextual factors may shape both perceived readiness challenges and expectations toward AI diagnostic systems.

Second, the present study focuses on the conceptual development of the proposed diagnostic artefact rather than its full implementation. As a result, the findings primarily reflect expert expectations and perceptions rather than observed system performance in real organisational environments. Additionally, while the study adopts a Design Science Research perspective, the current stage of the research corresponds mainly to the problem identification and design phase. Further work is required to empirically evaluate the artefact and assess its effectiveness compared to existing readiness assessment approaches. Future research should therefore focus on testing the proposed system in practice, ideally across different organisational contexts, in order to better understand its applicability and limitations.

Ethics Statement: This research involved semi-structured interviews with industry experts. Participation in the study was voluntary and all participants were informed about the purpose of the research prior to the interviews. Interviewees provided informed consent to participate in the study and to allow anonymized use of their responses for research purposes.

AI Declaration: AI assisted tools were used to support language editing and clarity.

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