

A MULTI-AGENT FRAMEWORK FOR AI READINESS ASSESSMENT WITH ADAPTIVE SURVEYS AND PUBLIC DATA INTEGRATION

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Purpose: Organizations increasingly rely on artificial intelligence, yet most assessment tools used to evaluate AI readiness still depends on static surveys. The objective of this research is to validate Agentic AI diagnostic approach to increase effectiveness of organization AI readiness assessment.

Design/methodology/approach: This paper introduces an Agentic AI diagnostic framework that replaces questionnaires with adaptive, conversational data collection system. The proposed approach combines self-reported information with external public sources (OSINT), delivering current state and recommendations for further AI implementation. The proposed research will be conducted using the Design Science Research methodology.

Findings: The literature review identifies key challenges related to static surveys method: declining response rate, respondent fatigue and failed value proposition. As result static interviews may produce low-quality, subjective and incomplete data.

Research limitations/implications: Research limitations are related to: AI readiness indicators changing with dynamic AI development and need to ensure ethical, governance and trust for proposed solution.

Practical implications: If research hypothesis confirmed, multi-agent diagnostic system to be used in organizational AI readiness evaluation allows organizations drive assessments tailored to their needs. It is especially valid for mid-size and SMB companies, who usually have limited access to the assessment tools. Additionally the proposed framework, after successful validation, can be further adjusted to other areas of organizational assessment.

Originality/value: The proposed Agentic AI diagnostic framework replaces questionnaires with adaptive, conversational data collection system. The system combines self-reported information with external public sources to better assess current AI readiness status and propose recommendations for further AI implementation tailored to the organization needs. We describe a multi-agent architecture as a reference implementation, together with research plan and methodology.

Keywords: Agentic AI; AI readiness; Adaptive surveys; OSINT integration; Design Science Research.

Category of the paper: Research paper.

1. Introduction

Artificial intelligence (AI) has emerged as one of the fastest-growing and most transformative technologies of the past decade, with a profound and accelerating impact across industries. According to industry forecasts from IDC (IDC, 2024 report), AI is projected to contribute \$19.9 trillion to the global economy by 2030, representing approximately 3.5% of global GDP. The significance of AI is frequently compared to historical technological breakthroughs such as the steam engine, electricity and the personal computer. While such projections underline AI's economic potential, realizing this value depends less on the technology itself and more on the organizational capacity to adopt and integrate it effectively. Artificial intelligence has moved from a discrete technology investment to a general-purpose capability that reconfigures how organizations sense opportunities, learn, and execute. In this sense, "AI maturity" for an organisation is less a stock of assets and more a flow of experimentation, data stewardship, model lifecycle management, and human capital development. This approach is similar for all key technology transitions (Teece et al., 1997).

Organizations face increasing pressure to adopt AI technologies (Sullivan, Fosso Wamba, 2024, Wodecki, 2018) while navigating uncertainty, skill gaps and organizational inertia. In such environment proper assessment of current state of organisation readiness for AI technology is important element to identify gaps and define next steps (Tehrani et al., 2024). There are already frameworks and models available on the market. The Technology–Organization–Environment (TOE) Framework, developed by Tornatzky and Fleischer (1990), is widely used to assess an organization's readiness to adopt new technologies in general. Another example is Capability Maturity Model Integration (CMMI) developed at the Software Engineering Institute of Carnegie Mellon University (2002) supporting adoption of AI usage. There are also more recent models like AI Readiness Index (AIRI) and AI Maturity Frameworks (e.g., from Gartner, McKinsey, or IBM). These methodologies typically involve structured surveys, expert interviews or workshops that capture the organization's status at a given moment, offering a maturity score or classification. However, they often neglect the fact that AI integration is a highly dynamic process, influenced by rapid technological advancements, evolving market demands, internal capability development and cultural shifts. From perspective of the recommendations, existing models tend to deliver standardized recommendations, lacking the flexibility of adaptation to an organization's specifics. There is also significant difference between large organisations and small and medium companies (Ayinaddis, 2025; Moeuf et al., 2018). For large companies they have often dedicated department focusing on Innovations, including AI implementation. They work with consulting companies to help them with understanding current state of AI readiness and develop strategy moving forward. For small and medium companies process is much less defined (Schwaeke et al., 2025) and in many cases they depend on in-house AI enthusiast, who treat AI implementation as his/her job+.

Traditional assessment approaches, typically based on manual questionnaires and interviews, are time-consuming, subjective, and often poorly aligned with real-time organizational dynamics. This project addresses a need for a scalable, intelligent and dynamic approach to evaluating and enhancing AI readiness. By introducing a self-adaptive Agentic AI system that integrates both OSINT (e.g., public data, news, company reports) and validated questionnaire frameworks (e.g., TOE, AIRI), the project aims to bridge the gap between assessment and actionable guidance. Furthermore, developing such a system will allow managers to shift from reactive to proactive AI strategies, supported by automated, context-aware insights.

The proposed research will be conducted using the Design Science Research (DSR) methodology (Hevner et al., 2004; Peffers et al., 2007) and following hypothesis will be validated:

- H1: The proposed Agentic AI system will demonstrate comparable or superior effectiveness in assessing organizational AI readiness compared to manual assessments based on existing readiness model.
- H2: Integrating Open Source Intelligence with questionnaire-based data increases the depth and reliability of organizational AI readiness assessments.

2. Literature review

Jöhnk, Weißert, and Wyrcki identify organizational AI readiness as a multidimensional construct consisting of strategic alignment and vision, availability of resources and technical capabilities, internal knowledge and skills, supportive organizational culture, data and ethics governance conditions. Collectively they determine an organization's readiness to adopt and benefit from AI technologies (Jöhnk et al., 2021). To be able to measure it effectively we need well proven models and quality data to feed the model. Recent research shows that conventional data collection methodologies, particularly surveys, are currently facing a systemic crisis. This is visible through a constellation of interconnected issues, including persistently declining participant engagement, escalating respondent fatigue and limited value of participation. Since our diagnostic system relies on survey instruments as one of its core data sources, understanding these limitations is crucial for designing an adaptive methodology. This section critically reviews why current survey methods are no longer efficient and propose potential improvements.

2.1. Declining response rates

Several researches indicate decades-long decline in survey response rates across nearly all modes of data collection signals a systemic challenge to the validity of survey-based research. This trend is connected with perception of academic and social surveys as inherently "biased", transforming non-response into a form of protest. The widespread adoption of online surveys, while offering significant gains in cost-efficiency and scalability, has paradoxically failed to resolve this engagement crisis (Daikeler et al., 2020). Multiple meta-analyses show that an average response rate for online surveys at approximately 44.1% (Wu et al., 2022), drastically falling short of the 80% benchmark, often recommended by governmental bodies for ensuring sample representativeness. In-person interviews with well selected participants allows to achieve much better results (West et al., 2018) but have much higher cost and limited ability to scale, especially in case of smaller organisations.

Such low response rates introduce a significant risk of nonresponse bias. This bias occurs when the segment of the population that chooses to respond is systematically different from the segment that does not. This compromises the research findings' generalizability. Research based on unrepresentative samples risks producing findings that fail to reflect the experiences of non-responding groups, which can create a negative feedback loop that reinforces the public's perception of bias and deepens their disengagement from the research process (Scheaf et al., 2023).

2.2. Perceived burden and respondent fatigue

Beyond the initial decision to participate, the quality of participation itself is heavily influenced by the respondent perceived "cost of participation" (Kunz, Gummer, 2025). Survey methodology literature distinguishes between objective burden (measurable characteristics like length) and perceived burden (the subjective experience of that effort), with research increasingly indicating that perceived burden is the more critical factor influencing respondent behaviour and data quality. Traditional surveys often impose significant burden through complex question structures and lengthy questionnaires, which directly impacts response quality and can lead to lower engagement and low quality responses (Jeong et al., 2023). This is valid for all types of surveys, with the most scalable method (online surveys) being highly susceptible to the degrading effects of fatigue, trading convenience for data quality.

The consequences of fatigue are mostly impactful for data quality. This is visible by an increase in ambiguous or "don't know" responses, a higher rate of skipped questions and "straight-lining" (selecting the same answer repeatedly without consideration) (Ward, Meade, 2023).

2.3. The failed value proposition

To understand declining engagement, it is crucial to apply Social Exchange Theory, which posits that individual actions are motivated by the expected rewards relative to their costs (Homans, 1958; Greenberg, Dillman, 2023). In the context of a survey, participation is maximized when costs (time, cognitive effort, privacy concerns) are minimized, rewards are maximized, and the respondent sees value from the participation. From this perspective, it becomes clear that the traditional survey model largely fails the social exchange test. It is a transaction heavily directed toward the researcher, maximizing costs for the respondent while offering minimal, often intangible, rewards in return. This imbalance contributes to declining engagement, as participants increasingly view surveys as extractive interactions rather than reciprocal exchanges. Research on survey participation shows that respondents are sensitive to fairness and frequently disengage when they feel that researchers simply “take” their time and insights without offering value in return (Singer, Ye, 2013). At the same time, methodological analyses demonstrate that poorly designed self-report instruments amplify risks of common method bias and superficial responding, further undermining the validity of the collected data (Podsakoff et al., 2024).

The failure to deliver value proposition for participants results in high nonresponse or the submission of superficial answers. This undermines the willingness of individuals to put genuine thought into their responses, thereby threatening the overall reliability and validity of the gathered data.

3. Problem statement and option to address the problem

Key challenges related to typical survey methodologies are declining engagement, eroding trust, and accumulating respondent burden. These issues directly lead to lower response rates and degraded data quality, threatening the validity of the results. This establishes a clear need for innovation that fundamentally reimagines the research interaction as a reciprocal value exchange, placing the respondent’s experience and benefit at the center of the process.

Artificial intelligence usage has the potential to change survey process from a static, one-way questionnaire into a responsive interaction that adapts to the respondent while maintaining methodological control. Several researches focus on chat usage to achieve this objective (Zarouali et al., 2024; Barari et al., 2025). Proposed research will focus rather than a single, defined model that asks questions and records answers, on multi-agent architecture distributing roles across coordinated specialists. Various agents can be implement focusing on specific areas, like an agent focusing on explanation of intent of questionnaire and specific questions or an agent monitoring the respondent engagement level. When these agents operate under explicit

intervention policies with version control and logging, the system can improve respondent experience and data quality while preserving standardization and comparability.

In practice, this enables responsive interviewing that reduces cognitive load, increases comprehension of complex items, and lowers break-off rates, while preserving standardization through explicit intervention policies and transparent logs. Agentic setups can also deliver immediate, non-directive value to participants (for example neutral summaries or benchmarked feedback), which may strengthen trust and longitudinal retention without compromising instrument fidelity. At the data layer, agents can coordinate data collection, calibrate assistance intensity and trigger targeted probes, creating a closed loop that links user experience metrics with classical indicators of data quality (item nonresponse, straight lining and construct validity).

However, the same affordances introduce nontrivial challenges. First, there is a risk of an “AI interviewer effect”: even subtle clarifications or examples can shift response distributions, threatening measurement invariance across modes and waves. Second, reproducibility is fragile without strict versioning, prompt governance and intervention caps, drift in foundation models or policies can erode comparability over time. Third, transparency and consent must be elevated: respondents should know when and how agents intervene, what is logged, and what immediate feedback is algorithmically generated. Fourth, fairness and accessibility require active design of language style, reading level, and turn-taking rules. Finally, security and privacy concerns intensify when agents process open-ended text or sensitive business data, calling for on-device processing where feasible, minimal data retention and independent audits.

4. Methods

The planned research addresses a growing challenge in management sciences: how to systematically and dynamically assess an organization’s readiness to adopt new technologies (Uren, Edwards, 2023), particularly Artificial Intelligence. As AI continues to transform operational models, decision-making processes, and innovation strategies, it becomes essential to equip organizations with diagnostic tools and methodology, that are not only reliable, but also adaptive, scalable and capable of synthesizing diverse sources of information. The proposed solution is a novel, intelligent artefact based on Agentic AI, combining structured diagnostic models with open-source intelligence (OSINT) and large language model (LLM) driven reasoning. During the research following research questions will be addressed:

RQ1: How can Agentic AI be effectively used to assess organizational maturity for AI implementation by combining OSINT and survey methods?

RQ2: What factors and metrics should be considered in assessing organizational maturity, and how to combine data from open sources and survey responses in the AI maturity study?

RQ3: To what extent can automatic, AI-generated recommendations based on maturity results support organizations in identifying gaps and improving their readiness for AI?

The Design Science Research (DSR) methodology (Hevner et al., 2004; Peffers et al., 2007) provides a robust framework for addressing complex, real-world challenges through the design, construction and evaluation of artefacts that have both practical utility and theoretical relevance. DSR has gained increasing recognition in the fields of information systems, organizational studies and management sciences, where the boundaries between technological development and strategic decision-making are becoming increasingly fluid. This methodology is particularly appropriate for projects focused on building and deploying AI driven solutions, as it allows the researcher to iterate between theory, system development and empirical testing in applied contexts. The research will follow the structure proposed by Hevner and Peffers, incorporating the following interrelated phases:

- Problem identification and definition of objectives (combined into one phase) – analysing limitations of current diagnostic approaches and identifying real-world readiness gaps; outlining the requirements and success criteria for a useful and generalizable artefact.
- Design and Development – engineering the Agentic AI system through iterative prototyping.
- Demonstration and evaluation (combined into one phase) – testing the system in organizational settings, with both technical and managerial feedback loops.
- Conclusions and Communication of results – define theoretical insights based on results and publish findings in peer-reviewed venues.

Table 1.

Research plan based on Design Science Research methodology

| | Name | Focus area | Activities |
|--------------------------|--|--|--|
| Phase I Months 1-4 | Problem Identification & Requirements Analysis | Establish the conceptual, technical, and organizational basis for the artefact | <ul style="list-style-type: none"> • A systematic literature review of maturity models used in technology and AI adoption. • Comparative analysis to select the most appropriate dimensions and metrics for readiness assessment. • Interviews with decision-makers in companies to capture organizational needs and pain points. • Mapping of OSINT sources. • Data governance process definition. |

Cont. table 1.

| | | | |
|------------------------------|---|--|---|
| Phase II Months 5-12 | Design & Development of the Agentic System | System construction and prototype development | <ul style="list-style-type: none"> • Building the modular architecture for the diagnostic system. • Implementation of Agent modules. • Configuring the Agentic AI logic using the ReAct framework. • Creating a recommendation engine that links readiness profiles to tailored managerial actions and change management strategies. • Designing a user interface. |
| Phase III Months 13-20 | Demonstration & Evaluation | tests the artefact in real organizational environments, assessing both technical performance and user value | <ul style="list-style-type: none"> • Pilot studies in 2-3 organizations. • Data collection through real-time use of the system and parallel manual assessments conducted by experts for benchmarking. • Quantitative evaluation using statistical methods to compare accuracy, consistency, and reliability. • Qualitative evaluation through expert interviews, focus groups, and usability testing. • Generalization analysis. |
| Phase IV Months 21-24 | Theoretical Generalization & Dissemination | insights are synthesized, findings are published, and the tool is prepared for academic and practical dissemination | <ul style="list-style-type: none"> • Refinement of the artefact based on feedback and pilot results. • Theoretical modelling of how Agentic systems can influence digital maturity management. • Preparation of scientific publications. • Open-access dissemination of methodological guidelines, system logic, and lessons learned to support replication and further research. |

There are several recent adoptions of DSR in addressing organisation challenges related to technology implementation (Tuunanen et al., 2024) and frameworks how to use them effectively (Australian National University, Australia et al., 2020). By following DSR framework, we will ensure transparency of the research process (Hevner et al., 2024). Additionally, the project not only will deliver a functional tool but also will contribute to the academic discourse on how intelligent systems support strategic decision-making and quality improvement in organizations. This methodological choice ensures that the developed artefact is both practically deployable and theoretically grounded, addressing the identified limitations of current readiness frameworks.

The artefact at the heart of this project is an Agentic AI diagnostic system, based on multi-agent system, designed to assess an organization's readiness to adopt AI. A multi-agent system (MAS) is a software architecture in which multiple autonomous agents, computational entities with distinct goals, perceptions, and policies, collaborate within a shared environment to solve tasks that exceed the scope of a single program (Sapkota et al., 2026; Guo et al., 2024). Agents can be homogeneous or role-specialized (e.g., orchestration, domain questions, compliance), and coordinated via centralized schedulers or decentralized protocols (request-reply, publish-subscribe, contract-net). Core benefits include division of labour, parallelism and fault tolerance. Core challenges include coordination overhead, credit assignment and maintaining global consistency when agents adapt locally. Practical MAS deployments rely on service discovery and shared ontologies for semantic interoperability, plus governance layers for access

control, versioning, logging, and auditability. Proposed research, will implement agent reasoning and tool use with the ReAct framework (Yao et al., 2023), which interleaves deliberation (“reasoning”) and external actions (e.g., database queries, API calls) under explicit stepwise policies. ReAct provides a transparent scaffold for planning, evidence retrieval, and intervention control, enabling agents to justify actions, hand off subtasks and recover from failures while preserving methodological control. For AI augmented data collection, this MAS enables responsive interviewing (adaptive explanations, fatigue monitoring) within predefined intervention caps and standardized logs, so user experience can improve without sacrificing comparability, safety or reproducibility.

5. Proposed solution

Unlike static models, the artefact from this project integrates internal diagnostic data (via validated survey instruments) and external public data (via Open Source Intelligence), analyzed through a Large Language Model (LLM) based reasoning engine. This approach reflects a broader shift in the management sciences toward intelligent decision-support systems that learn from their environment and provide dynamic, tailored recommendations.

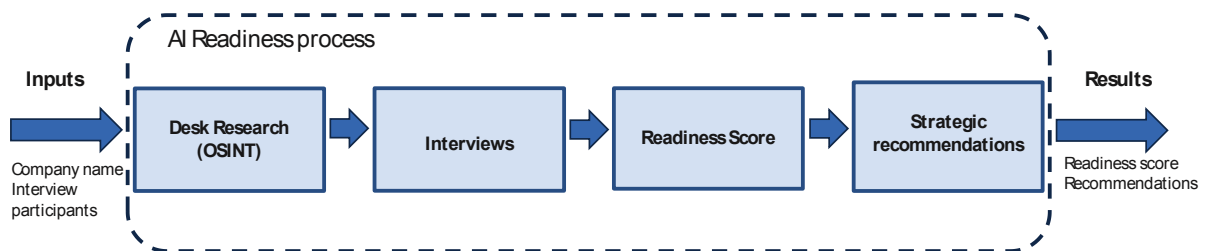


Figure 1. Flow of the proposed AI readiness process.

To achieve this objectives multi agent system will be implemented. The system utilizes several agents that collaborate to gather data, interact with the participant, score maturity, and generate recommendations:

- Supervisory Agent - manages the input interface and manages all processes within the system.
- OSINT Collection Agent - gathers public data from websites, APIs, and reports related to AI readiness aspects. Its task is to search publicly available resources based on company data (name, segment, NIP/REGON) to identify important information for assessing the company's AI technology utilization maturity.
- Initial Survey Agent - performs the initial review with the participant. Its task is to conduct a preliminary conversation to understand the respondent's role, assess their expectations and concerns regarding AI, and determine the areas of the main survey that require focus.

- Readiness Survey Agent - uses a scoring model to drive the questionnaire with the participant. We are looking at 3 possible options to run survey:
 - static text survey using predefined set of questions,
 - dynamic text survey with questions being adjusted based on responses and OSINT data,
 - adaptive voice survey with questions being adjusted based on responses and OSINT data.

Final decision on implementation will be based on outcome from expert interviews planned as first step.

- Readiness Scoring Agent - synthesizes the results from the survey and OSINT data to detect patterns and contextual alignment and provides the readiness score. Its main task is to prepare an integrated report assessing organizational maturity by utilizing OSINT data and respondent answers and assessing consistency (cohesion) between these sources.
- Recommendation Generator Agent - uses Large Language Models (LLMs) and ReAct-style prompts to generate strategic recommendations. Its task is to prepare a report detailing short-term (Quick Wins) and long-term developmental actions to enable effective AI implementation.
- User Interface Agent presents the scoring and recommendations results to users and also gathers qualitative feedback about proposed information and survey process.
- Feedback and Learning Agent Collects usage data and feedback. Its function is to propose corrections and improve the reasoning capabilities of the other agents.

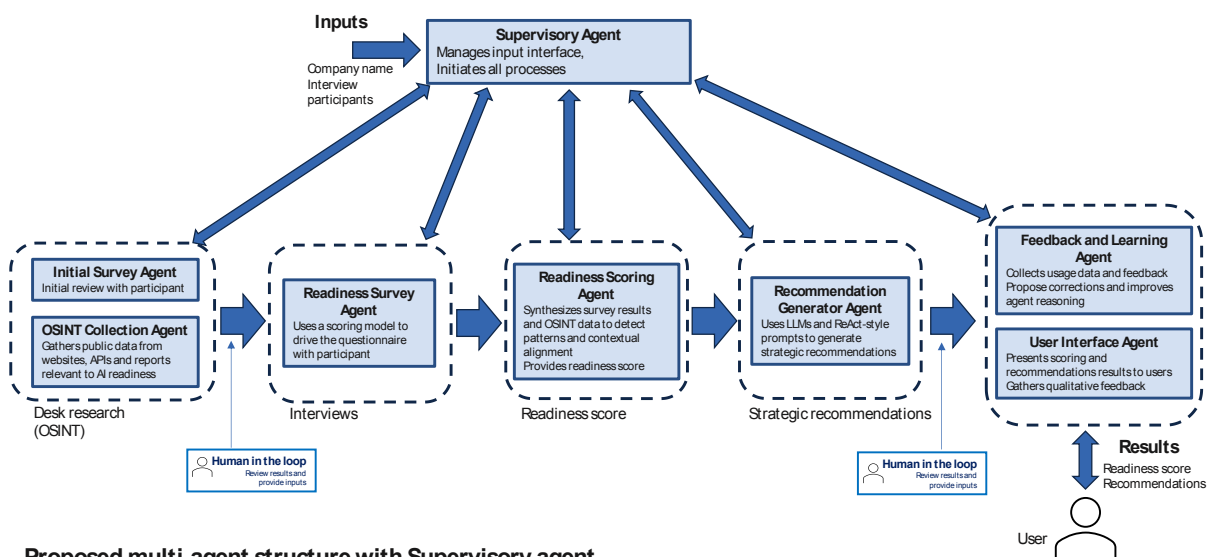
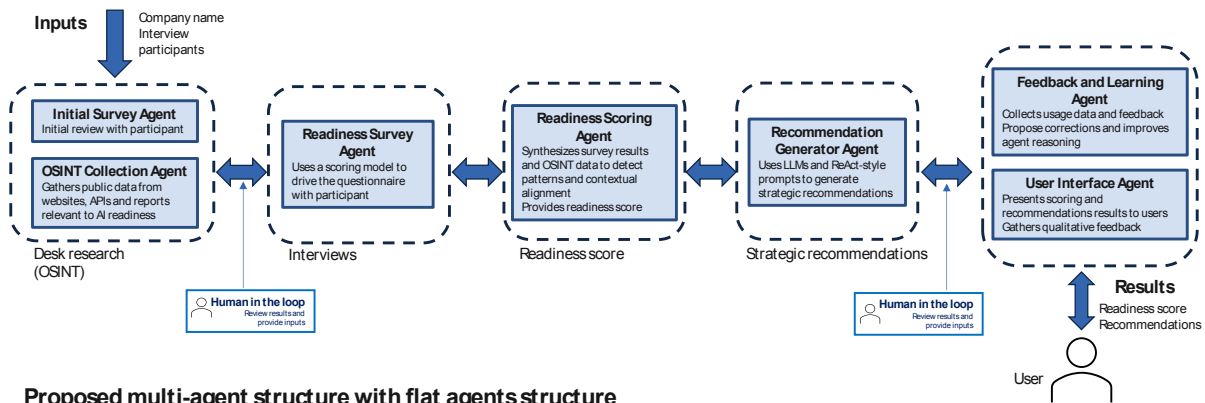


Figure 2. Proposed structure of multi-agent system for AI readiness scoring with Supervisory agent.

Multi-agent architectures are developing very fast and offers various possible implementation options. To compare effectiveness the research will include both above presented structure with Supervisory agent as well as flat agent architecture presented below, where entire communication is happening between participating agents.



Proposed multi-agent structure with flat agents structure

Figure 3. Proposed structure of multi-agent system for AI readiness scoring with flat agents structure.

The comparison between these two architectures will be done as part of the artefact evaluation phase. It will be based on following criteria: variance measurement in assigned maturity levels or recommendation sets for each architecture when assessment done for the same company and length of the process and participants satisfaction comparison.

The assessment starts with input data: company name and names of interview participants. As an outcome participants will receive scoring results and recommendations, both tailored for participating company.

After OSINT data collection and before results communication to the participants we have “Human in the loop” step allowing researchers to review the data and validate ability to move forward with next steps. Human validation is a safeguard, which will be used during testing phase with selected companies to test quality of the proposed approach. In case of broader adoption “human in the loop” element will be removed as otherwise would limit scalability of the artefact.

Having defined structure of the solution the study will start by expert interviews to collect additional inputs and comments helping to validate proposed structure and proposed survey options in the system before final implementation and testing with organisations. Expert Interviews will be done with selected leaders having practical knowledge and expertise in both managing organisations and technology usage.

6. Discussion and future research

Proposed research contributes to the growing discussion on how organizations can effectively assess and develop readiness for artificial intelligence adoption. Existing approaches to AI readiness often treat adoption as a static condition, overlooking the dynamic feedback loops that characterize modern AI driven organizations. By integrating Design Science Research methodology with development of Agentic AI and open-source intelligence, it offers both a theoretical and methodological framework for understanding readiness as a dynamic capability system rather than a fixed state. The following discussion reflects on the project's implications and proposes specific directions for future research.

6.1. Organizational Readiness in the age of AI

Traditional readiness frameworks view technology adoption as a linear process, starting from awareness, moving to implementation and standardization (Appio et al., 2021). However, the increasing autonomy and adaptivity of modern AI systems challenge this linearity. The proposed multi-agent artefact reframes readiness as a continuous, feedback-driven process, where assessment and capability development occur simultaneously. This extends the theoretical understanding of readiness by integrating principles of learning systems, feedback loops, and data driven adaptation.

Future research could build on this by examining how organizations use and benefit from intelligent diagnostic artefacts. How repeated interactions with adaptive systems influence organisation dynamics, particularly managerial impact, learning behaviour or decision making process.

6.2. Methodological implications in surveys

Beyond theoretical implications, the proposed artefact also carries methodological consequences for how readiness is studied. We covered in details current survey limitations - static, one-way questionnaires are increasingly insufficient for capturing complex, context sensitive processes like AI adoption. By using agentic conversational interfaces within diagnostic systems, we believe, we can design instruments that are both scalable and responsive (Barari et al., 2025). By following DSR framework we will maintain methodological rigor while improving participant engagement (Hevner et al., 2024).

Future research should empirically test these interactive designs through controlled field experiments and comparative studies. These research should help understand how AI based interactions affect response quality, perceived trust and data richness. This could help to further develop framework of AI assisted research methodologies.

6.3. Ethical, Governance, and Trust Considerations

Finally, as these systems become more autonomous, their methodological promise must be balanced by careful attention to ethical and governance challenges. As AI becomes critical part of research and management processes, issues of transparency, fairness, and trust gain more importance (Jobin et al., 2019). Agentic systems that process sensitive business or personal data must balance personalization with privacy. This will be important element while designing Agentic AI system. During our research we will continuously track level of acceptance of the artefact by research participants.

Future research should further address the ethical design principles of such systems, including explainability, data minimization, and algorithmic accountability. It should be done with objective to develop standardized governance frameworks for AI based diagnostics to ensure responsible use and increase organizational trust.

7. Summary

Artificial intelligence is rapidly growing its importance in every aspect, including organization's effectiveness. This study critically reviews current organizational diagnostic practices, with particular attention to widely used survey based assessment methods. The literature reviewed consistently demonstrates declining response rates, rising cognitive burden, survey fatigue, and growing risks of superficial or biased self-reported data. Existing research provides strong evidence that traditional static questionnaires struggle to deliver reliable and valid organizational insights in complex, rapidly evolving technological contexts. However, prior studies largely stop at diagnosing these problems. They offer limited guidance on how next-generation diagnostic systems could practically overcome these limitations, particularly in organizational settings requiring contextual interpretation, clarification of meaning, and triangulation across data sources. Moreover, current AI readiness models rely predominantly on static survey instruments, thereby inheriting the very weaknesses identified in the survey methodology literature.

The article introduces a new conceptual approach: a multi-agent, conversational diagnostic system that replaces static questionnaires with adaptive AI driven interviews and external data integration, allowing verification and richer context. This concept is based on fact that effective organizational diagnostics must shift from one directional data extraction toward interactive processes. Additionally organizational readiness assessment should be a dynamic, conversational and multi-source diagnostic activity rather than a static measurement exercise.

As organizations increasingly adopt AI technologies, reliable readiness assessment becomes critical in other areas as well, like strategic decision-making, investment prioritization and risk management. The proposed framework, after successful validation, can be further adjusted to other areas of organizational assessment, including digital transformation audits, capability maturity evaluations and change readiness diagnostics.

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