Measurement Approaches for Evaluating the Technological and Organizational Factors of Artificial Intelligence Implementation in Businesses

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Abstract: The empirical literature has identified dozens of specific factors, such as organizational and technical readiness and many others, which positively influence the implementation of artificial intelligence (AI) in innovative businesses. The aim of this article was to compile a theoretical review of measurement instruments for these factors and to discuss their qualities, strengths, and weaknesses. Using a systematic literature review approach, we identified dozens of articles describing the factors in question, within which we analyzed specific measurement instruments and compiled a systematic overview of them. We found that the methods of measurement, the instruments, and the indicators used to describe and assess the status and level of these factors differ in nature and design and vary in their explanatory value and measurement validity. Self-report questionnaires and subjective expert assessments are combined with objective financial indicators. A systematic and comprehensive overview of measurement tools will provide managers with a practical aid in the process of implementing AI, thereby increasing the likelihood of successful AI implementation. At the same time, it will enable researchers to improve the existing framework and help create better, more informative measurement instruments.

Keywords: AI implementation, AI implementation factors, measurement tools
JEL Classification: O32, M15, M21

1 Introduction

In recent years, artificial intelligence has achieved exceptional performance across a variety of cognitive and practical tasks, which has contributed to its widespread adoption among individual users (Inkpen et al., 2024). At the same time, its implementation in enterprise solutions has, in practice, lagged behind individual use. There are multiple reasons for this; among the most frequently cited are difficulties integrating it into business processes (Haefner et al., 2023). This lag at the organizational level has spurred intensive scholarly efforts to examine and uncover the factors influencing the adoption of artificial intelligence. the empirical literature has identified dozens of distinct factors that affect AI adoption, either positively or negatively (Kar, Kushwaha, 2023; Khanfar, et al. 2025). These factors operate at the level of the initial decision, the implementation processes, and overall success. These factors and barriers are diverse and can be categorized into several groups. In this article, we focus on two broad groups that Khanfar and colleagues (2025), in a systematic review, refer to as organizational factors and technical factors.

However, if we aim to successfully implement artificial intelligence in a specific enterprise, it is essential to examine the organization's level of readiness, more precisely, the level and status of those factors that have been shown to affect the success of AI implementation. These factors are, however, often described in fairly general terms, such as organizational readiness, which raises a practical question for management: how can this organizational readiness be meaningfully measured?

Empirical studies examining these factors usually report the specific measurement instruments by which they were operationalized. A review of this literature reveals considerable variability and diversity in the instruments employed. Some studies rely on self-report questionnaires (Agarwal, 2022; Tjebane et al., 2022), others on structured interviews (Campion et al., 2022; Neumann et al., 2024), expert assessments (Wang K. et al., 2021), or approaches that gauge readiness using objective financial indicators or other methods. These instruments also differ in measurement quality, specifically in terms of validity, reliability, objectivity, and sensitivity. They likewise vary in the demands they place on data collection and administration with respect to time, staffing, and the organization of data collection. From both a scholarly and managerial

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standpoint, it is important to know which measurement instruments have been used empirically to assess the level of implementation factors and an enterprise's readiness with respect to the specific factor under study. Accordingly, the aim of this article was to compile a theoretical review of measurement instruments for these factors and to discuss their qualities, strengths, and limitations.

2 Methods

In the first step, we conducted a systematic literature review to identify empirical articles that describe factors related to the implementation of artificial intelligence in enterprises and that report explicit measurement instruments used to operationalize these factors. The search targeted instruments used to assess organizational factors (for example organizational readiness) and technological factors (for example technological readiness), including questionnaires, interview protocols, expert elicitation matrices, and secondary data indicators. We searched the following bibliographic databases: Scopus, Web of Science, ProQuest. The search covered the period from 2020 to 2025. The database searches retrieved 524 records. After deduplication, 144 duplicates were removed, and 380 unique records remained. Title and abstract screening excluded 323 records as clearly irrelevant to AI implementation in organizational settings or without any operationalized organizational or technological factors. We assessed 57 full text articles for eligibility. Of these, 41 were excluded because they did not report an explicit measurement instrument or operationalization, were not empirical, or did not focus on organizational or technological determinants of AI implementation. An additional 6 studies were identified through backward and forward citation searching and supplementary searches conducted by the second reviewer. In total, 22 studies were included in the synthesis and instrument comparison.

We included peer reviewed empirical studies that examined AI adoption or implementation in organizational settings that reported at least one technological or organizational factor relevant to implementation and specified the measurement instrument or operationalization used for that factor. We excluded review articles (systematic reviews and meta-analysis), purely conceptual or theoretical papers, editorials, and studies that discussed factors without describing how they were measured. Furthermore, the review process involved two independent reviewers at all critical stages, including study selection and data extraction.

Records were deduplicated prior to screening. Titles and abstracts were screened against the eligibility criteria, followed by full text assessment of potentially relevant articles. Disagreements were resolved through discussion.

We conducted quality appraisal at two levels. At the study level, we assessed methodological quality using a design appropriate checklist, and used the appraisal to interpret the strength of evidence rather than to exclude studies. At the instrument level, we evaluated measurement approaches using a structured rubric with five criteria: construct clarity, evidence of measurement quality, transparency and reproducibility, practical burden of administration and scoring, and decision usefulness for managers. In addition, a formal quality assessment of the included studies has been incorporated using predefined and theoretically grounded criteria appropriate to the study designs identified.

3 Research results

In the following two tables, we provide an overview of the individual factors and measurement instruments used by the authors of empirical studies to assess the level and state of each factor influencing the adoption of artificial intelligence. The tables indicate the type of research conducted, whether qualitative or quantitative, followed by the specific measurement instrument employed and the sample on which it was applied. The "Aim of the study" column describes the objective of each study, while the final column lists the theories and theoretical foundations on which the respective article was based.

Table 1 Overview of measurement instruments for the organizational readiness factor, competence

Study	Qualitative or Quantitative methodology	Measurement tool	Sample	Aim of the study	Theoretical background
Agarwal (2022)	Quantitative	4-item organizational preparedness scale, 5-point Likert scale	210 human resource management employees	analyze AI adoption antecedents, examining how organizational readiness, perceived benefits, and technical expertise collectively influence AI adoption	Task-Organization-Environment (TOE) Framework and Task-Technology Fit (TTF) Model

Campion et al. (2022)	Qualitative case study approach	in-depth, semi-structured interviews	24 individuals top-level leadership, middle managers, bottom-level analysts	understanding the challenges faced by interorganizational collaborations in adopting AI tools and implementing organizational routines to overcome these challenges	Interorganizational Collaboration Theory/Organizational Routines Theory
Hradecky et al. (2022)	Qualitative, exploratory approach	A battery of questions for interviews Semi-structured Interviews	seventeen senior managerial representatives from exhibition organizations across nine Western European countries	comprehensive understanding of the factors influencing AI adoption readiness in the exhibition sector, offering insights into both organizational and individual perspectives on new technology adoption	Technology-Organization-Environment (TOE) Framework combined with Technology Readiness Index (TRI)
Neumann et al. (2022)	Qualitative	Semi-structured interviews	17 individuals involved in AI projects across eight Swiss public organizations	comprehensive, adapted theoretical framework and a maturity model, operationalized through qualitative interviews to measure organizational readiness and AI adoption stages	AI-adapted Technology-Organization-Environment (TOE) framework, complemented by a five-level AI maturity model
Tjebane et al. (2022)	Quantitative	Questionnaire	150 construction professionals/ South Africa	identify existing organizational factors influencing AI adoption in the construction and allied industries	Not specified/ systematic literature review
Chatterjee, Rana, et al. (2021)	Quantitative	Questionnaire	340 top/middle-level professionals from manufacturing & production firms (India); small/medium/large organizations	Identify antecedents of AI adoption, assess readiness, and test leadership support as a moderator	Integrated TAM–TOE model (TAM + TOE)
Jöhnk et al. (2021)	Qualitative	Semi-structured interviews; triangulation with literature/practitioner sources; focus-group card-sorting for validation.	25 AI experts (users & providers) across industries and firm sizes; purposive sampling.	Conceptualize organizational AI readiness and derive factors/indicators to guide AI adoption decisions.	Innovation/technology adoption (DOI, TOE, TAM/TRA/TPB) + organizational readiness for change / digital readiness.
Hogan et al. (2020)	Quantitative	Questionnaire	hospital pharmacy staff (pharmacists, interns, support); 64 at implementation	explore factors influencing acceptance of a pharmacy robotic dispensing system during implementation and over time	Extended Technology Acceptance Model (TAM/TAM2)

Neumann et al. (2024)	Qualitative, comparative multi-case	Semi-structured interviews	17 interviewees (internal/external project & programme leads, experts) across state-owned enterprises, ministries, regional agencies, and municipalities	Identify TOE factors that facilitate/hinder AI adoption across maturity stages in public organizations	AI-adapted TOE framework + AI maturity levels (time dimension)
Uren et al. (2023)	Qualitative	Semi-structured interviews	5 AI experts (business, development, research) across 14 interviews	Explain the AI adoption journey and propose a PPTD-with-TRL model to surface readiness factors for moving to operational AI	PPT/PPTD socio-technical lens
Saeed et al. (2024)	Qualitative	Interviews using a TOE+TRI-based guide; reflexive thematic analysis	27 senior representatives: 17 library managers + 10 registrars across Pakistani universities	Assess organizational readiness for AI in university libraries; surface factors to guide adoption.	Integrated TOE + TRI readiness lens
Polisetty et al. (2023)	Quantitative	Questionnaire (5-point Likert); includes 3-item AI readiness and scales for TOE, AI ethics, competitive advantage	866 manager-level employees from Indian SMEs (manufacturing-focused)	Identify TOE antecedents of AI adoption/readiness and test links to competitive advantage with readiness (med.) and AI ethics (mod.)	TOE with AI readiness (mediator) and AI ethics (moderator)
Mathagu (2024)	Quantitative	Questionnaire (5-point Likert);	CEOs/founders/managers/IT professionals	Identify & test critical factors influencing AI adoption in SMEs (UK) via SEM	TOE framework
Lada et al. (2023)	Quantitative	Questionnaire (7-point Likert); includes 4-item Organizational Readiness	196 SME owners/managers (Sabah, Malaysia), multi-sector; judgemental sampling	AI adoption in SMEs	Prior AI-adoption literature; internal/external (TOE-inspired) framing; not an explicit named-theory test

Source: Own processing

In the following table, we present an overview of measurement instruments for the technical/technological Readiness factor, competence.

Table 2 Overview of measurement instruments for the technical/technological readiness factor: competence

Study	Qualitative or Quantitative research	Measurement tool	Sample	Aim of the study	Theoretical background
Dora et al. (2021)	Mixed/decision-analytic case study; expert elicitation	Expert interviews to define CSFs; expert-rating poll (matrix)	15 experts (senior GMs, SC/logistics managers, IT officers, finance)	Identify & prioritize CSFs for AI adoption in food supply chains	TOEH (Technology–Organization–Environment–Human) integrating TOE/HOT
Chen et al. (2021)	Quantitative	Questionnaire (7-point Likert)	289 managers & IT engineers at major Chinese telecom operators	Identify/test success factors driving AI adoption in telecom using SEM	Integrated TOE–DOI framework
Pillai et al. (2020)	Quantitative	Structured questionnaire (5-point Likert); includes 4-item HR readiness scale	562 HR/TA managers & executives from IT/ITeS firms (Mumbai & Pune, India)	Identify predictors of AI adoption & actual usage for talent acquisition in IT/ITeS	Integrated TOE–TTF
Tang et al. (2020)	Qualitative	Open-ended interviews; narrative analysis	7 management-education academics (Instructor–Assoc. Prof.), purposive sample	Explore opportunities & challenges of using educational robotics across curriculum/pedagogy/technology	Vygotskian social constructivism; teachers' perceptions as adoption determinants
Wang Y. et al. (2021)	Qualitative	Semi-structured interviews + case documents/field visits; triangulated secondary data	3 heavy-manufacturing firms (China); 9 interviewees (technicians, product manager/director, AI team, partners)	Identify TOE-based drivers of AI adoption for digital transformation and propose an AI business model	TOE framework (with DOI/TAM family as background)
Wang K. et al. (2021)	Quantitative	expert-rating DEMATEL matrix (0–4 pairwise influence)	10 experts (industry, government, university; China)	Identify and model challenges to AI/IoT adoption in smart cities and their cause–effect relationships	methodology-driven (DEMATEL)
Arroyabe et al. (2024)	Quantitative	Digital capabilities index from Flash Eurobarometer	12 108 SMEs across 27 EU countries (CATI; stratified by size/sector)	Test how digital (technical) & innovation capabilities and business environment affect AI adoption (regression + ANN/tree models)	Dynamic Capabilities + Resource Dependency theories (integrated)
Rahman et al. (2023)	Quantitative	6-item B2BTR scale (7-point Likert)	217 employees/managers from South African B2B industrial manufacturers	Examine effects of technology readiness → ICT → AI-CRM, and links to relationship & social sustainability;	Dynamic Capability View (DCV) (RBV-based); ICT as mediator, industry dynamism as moderator

Source: Own processing

Across the included studies, the measurement approaches summarized in Tables 1 and 2 can be grouped into a small number of recurring instrument families. These families differ not only in format, but also in the type of evidence they produce, the biases they are exposed to, and their usefulness for managerial decision making.

Instruments most applicable in the practice and their limitations

First, short self report readiness scales use Likert type items to capture perceived preparedness, skills, or perceived ease of adoption. They are inexpensive and repeatable, but they are sensitive to social desirability, overconfidence, and common method bias. Second, extended survey batteries operationalize readiness as a multidimensional construct, often aligned with TOE derived dimensions. They improve construct coverage and analytical detail, but increase respondent burden and often vary in dimensional definitions across studies, which limits comparability. Third, qualitative diagnostics, such as semi structured interviews, multi case studies, and maturity models, elicit process detail and help identify bottlenecks and sequencing needs. Their outputs are highly actionable, but depend on interviewer skill and are harder to benchmark across firms. Fourth, expert elicitation and decision analytic matrices, including DEMATEL style approaches, are useful for prioritizing interdependent barriers and enablers, but their credibility depends on transparent expert selection and elicitation protocols. Fifth, secondary data indices approximate capabilities using externally collected indicators, enabling benchmarking, but often remain too coarse for firm level implementation planning.

Table 3 Interpretive comparison of instrument families and practical applicability and main limitations

Instrument family	Best practical use and typical outputs	Main limitations and requirements
Short self report readiness scales (Likert)	Rapid baseline and periodic tracking of perceived readiness or competence	Self report biases (social desirability, overconfidence) and common method bias; requires careful survey design
Extended survey batteries (multidimensional questionnaires)	Richer diagnostic survey for medium and large firms; outputs multiple readiness dimensions for benchmarking and modeling	Higher respondent burden; construct definitions vary across studies; requires statistical competence for interpretation
Qualitative diagnostics (interviews, case studies, maturity models)	Implementation planning and transformation programs; outputs bottlenecks, governance gaps, and sequencing guidance	Time intensive; depends on facilitator skill; lower comparability across organizations
Expert elicitation and decision analytic matrices (for example DEMATEL)	Prioritizing interventions when barriers interact; outputs ranked factors and influence structure	Credibility depends on expert selection and transparent elicitation; requires decision analytics capability
Secondary data indices and objective indicators	Benchmarking across sectors or countries; triangulation with internal assessments	Often too coarse for firm level planning; constrained by data availability and indicator validity

Source: Own processing

Table 3 summarizes how the instrument families differ in decision usefulness and feasibility. Questionnaire based approaches scale well, qualitative diagnostics offer higher depth for implementation planning, expert based matrices support prioritization under interdependencies, and secondary data indices are primarily useful for benchmarking.

4 Conclusions

The aim of our research was to produce a theoretical review of measurement instruments for implementation factors. Our review identified a diverse set of instruments. Quantitative tools in the form of questionnaires and qualitative tools, predominantly various forms of structured interviews are represented in roughly equal measure. Other forms of measurement are rare, for example an expert-rating DEMATEL matrix (Wang K. et al., 2021).

As for the scientific theories used to explain the adoption of artificial intelligence, we observe a progressive, gradual approach. In this approach, researchers first attempt to account for AI adoption using older models originally applied to the uptake of various technologies. The Technology Acceptance Model (TAM) is among the most fundamental and widely used. Its now insufficient and rather shallow capacity to explain the adoption of a new, complex technology such as AI has been addressed through continual refinement and extension. Newer and improved versions of the original TAM, such as the extended Technology Acceptance Model (TAM/TAM2), have also been used (Hogan et al. 2020). A similar pattern appears with other legacy models and theories employed to explain AI adoption, such as the Technology–Organization–Environment (TOE) framework (Mathagu 2024), supplemented by newer models like TOEH (Technology–Organization–Environment–Human), used by Dora et al. (2021). Our review also found active combinations of different theoretical approaches and models in an effort to explain AI adoption more effectively. For example, an integrated TAM–TOE model (TAM + TOE) (Chatterjee, Rana, et al., 2021). Likewise, we can identify combinations of TAM, TOE, and the Diffusion of Innovation (DOI) model (Wang Y. et al., 2021).

If managers are to succeed in implementing and deploying artificial intelligence within their organizations, it is essential that they have measurement instruments that help determine the level of readiness with respect to each specific factor. Our research revealed a fairly diverse range of tools currently available. Instrument choice should be driven by the decision context, time horizon, and internal analytical capacity. For rapid baseline assessment in firms with limited analytical resources, short self report readiness scales and compact questionnaires are typically the most feasible and most applicable in the practice because they minimize burden and can be repeated over time. For organizations planning multi month implementation programs, semi structured interview-based diagnostics and maturity models tend to be more actionable because they surface bottlenecks in governance, data, skills, and process integration. When prioritization among many interdependent barriers is required, expert elicitation and decision analytic matrices are useful, but only when expert selection and elicitation procedures are reported transparently. Secondary data indices are most appropriate for benchmarking across countries or sectors and for triangulation, but they should not be treated as sufficient for firm level readiness decisions.

Accordingly, a practical selection rule is to start with a low burden questionnaire to establish a baseline, follow with qualitative diagnostics in areas where the baseline indicates weaknesses or strategic uncertainty, and use expert-based prioritization methods when decision makers need to rank interventions under complex interdependencies.

Limitations of our study

Our review is could be constrained by the scope and quality of the primary studies included, meaning that any biases, methodological weaknesses, or inconsistencies in the original research are transferred into the synthesized findings. Despite the use of predefined standard scientific search strategies, relevant studies may have been omitted due to database coverage limitations or the exclusion of grey literature. Another limitation of our research and thus of our results is publication bias, which remains a persistent concern, as studies reporting statistically significant or positive results are more likely to be published and thus included in the review. We also report, as a limitation, our own subjective judgment in study selection, data extraction, and quality appraisal, although guided by standardized protocols, which may introduce reviewer bias despite our best efforts.

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