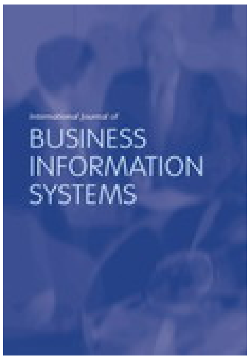

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Exploration and prioritisation of critical success factors in adoption of artificial intelligence: a mixed-methods study

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Exploration and prioritisation of critical success factors in adoption of artificial intelligence: a mixed-methods study

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Abstract: Artificial intelligence (AI) is becoming a strategic asset for businesses across all sectors. While most large companies have taken their first steps towards AI adoption, the success has remained strikingly limited. The current underdeveloped understanding of the critical success factors (CSFs) is argued to be one of the reasons for failing AI adoption. This study applies a mixed-methods approach, in which a broad information systems (IS) literature is systematically reviewed to identify CSFs relevant to AI adoption, including management support, business casing, problem orientation, data quality, data governance, cyber security and regulations. Next, an analytic hierarchy process (AHP) survey is combined with expert interviews to empirically rank and refine the identified CSFs across a multi-stage AI adoption model. The findings contribute to the scholarly discourse on CSFs relevant to AI adoption and help firms sharpen their focus and leverage their resources efficiently towards a more effective adoption of AI.

Keywords: artificial intelligence; critical success factors; CSFs; systematic literature review; SLR; analytic hierarchy process; AHP; expert interview.

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1 Introduction

Marked by increasing investments in artificial intelligence (AI) – driven initiatives and use-cases across different sectors, AI is maturing unprecedentedly both within and outside the tech domain (Borges et al., 2021; Bughin et al., 2017b). Nevertheless, the rate of sustainable adoption of AI-driven solutions has remained remarkably low (Fountaine et al., 2019; Hradecky et al., 2022). First, AI systems are becoming more complicated and less foreseeable (Zuiderwijk et al., 2021). Second, there are still many challenges regarding the performance of AI and expert systems (Davenport and Bean, 2019). Third, despite heavy investments, organisations often face a lot of challenges in adopting AI-based solutions for reasons including the scarceness of specialists in the AI field, the inadequacy of technological infrastructure, lack of organisational flexibility towards internal and external changes, intolerance of ambiguity, to name a few (Pillai and Sivathanu, 2020). Therefore, it is argued that notwithstanding the growing investments by more than 50% in 2018, our understanding of the AI-specific requirements or readiness factors to ensure successful organisational implementation is limited (Pumplun et al., 2019). More specifically, the critical success factors (CSFs) which affect AI adoption are not always apparent (Duan et al., 2019).

CSFs are studied within a wide range of domains, including enterprise resource planning (ERP) (Awa and Ojiabo, 2016); electronic health records (Standing and Cripps, 2015; Nikayin et al., 2014), customer relationship management (CRM) (Meyliana et al., 2016), training course projects (Fu et al., 2015), supply chain collaboration (Solaimani et al., 2015a; Solaimani and van der Veen, 2021), theses and dissertation repositories (Rasuli et al., 2018, 2019), smart homes (Solaimani et al., 2013, 2015b). In the context of AI adoption, CSFs can be defined as factors which are critical to achieving the desired outcomes, such as realisation, avoidance, tracking, or evaluation of an appropriate AI adoption level (Kachru, 2005). The adoption of any technology happens over time (Vargas and Comuzzi, 2020) and the value creation process is often a block box (Zand et al., 2015). In the case of AI, it starts with exploring the potential of the AI project and its value for the business (Niederman, 2021) and moves towards small-scale implementation with proof-of-concept and local deployment, and ultimately, full-fledge rollout often scaled across multiple business units (Hameed et al., 2012; Müller et al., 2018).

Despite several scholarly calls for more attention to critical factors contributing to success or failure of AI technologies, (e.g., Duan et al., 2019; Mehri, 2022; Mir et al., 2020; Yoon and Lee, 2018), a limited number of studies have focused on identifying and validating CSFs, in particular, factors relevant to AI adoption. Building on the existing literature on the adoption of AI, this study aims to:

1 identify the CSFs in this domain

2 empirically explore the priorities of the CSFs across the three stages of technology adoption, namely, exploration, implementation, and scaling.

These three stages are broadly recognised across numerous studies on technology adoption (e.g., Ng, 2020; Bose and Luo, 2011; Brock and Von Wangenheim, 2019). As such, this study contributes to the AI community by helping both scholars and practitioners focus on the most relevant values, capabilities, processes, and infrastructure while remaining heedful of the context-specific factors impacting AI adoption. The identified and empirically prioritised CSFs help firms sharpen their focus and effectively channel their effort in avoiding barriers and challenges across various stages of AI adoption.

The remainder of this study is structured as follows. The following section discusses the mixed-method approach applied in this study and provides a detailed account of how in this study, the literature on AI adoption is systematically reviewed to elicit CSFs and how the analytic hierarchy process (AHP) and expert interviews are triangulated to rank and refine the collected CSFs across various stages of adoption. Section 3 presents a vast array of CSFs relevant to AI adoption and provides empirically ranked CSFs across three phases of adoption. The study concludes by discussing the findings, the theoretical and practical implications, and the limitations and proposes several fruitful areas for future research.

2 Material and methods

This study adopts a mixed-methods approach to meet the multi-step objectives of collecting, prioritising and contextualising CSFs. The mixed-methods approach is an umbrella term for research combining multiple paradigms, such as scientific and interpretative, or analytical approaches, such as qualitative and quantitative (Harrington, 2014). In a mixed-methods study, one method's results inform the development of another (Christensen, 2022). In this way, the researchers are enabled to 'obtain convergence or corroboration of findings, to eliminate or minimise key plausible alternative explanations for conclusions drawn from the research data, and to elucidate the divergent aspects of a phenomenon' [Johnson and Onwuegbuzie, (2004), p.299]. This study uses a combination of systematic literature review (SLR), AHP, and expert interviews, elaborated in the following sections.

2.1 Identification of CSFs: SLR

As a first step, this study employed a SLR to draw a long list of CSFs on AI adoption from relatively dispersed academic and grey literature. Fink (2019, p.3) defines SLR as 'a systematic, explicit, and reproducible method for identifying, evaluating, and synthesising the existing body of completed and recorded work produced by researchers, scholars, and practitioners'. The data collection and review process is structured according to the three widely accepted steps of Tranfield et al. (2003), i.e., planning, conducting, and reporting the review, to ensure internal validity (Bodhi et al., 2021) (see Table 1 and Figure 1 for an overview of the SLR steps and process taken in this study). The leading search engines, including Scopus, Google Scholar and EBSCO, are used to collect relevant publications. Besides, the top-tier business and IS/IT publishers' repositories, including the *MIT Sloan Management Review*, *Information Systems Research*, *MIS Quarterly*, *Journal of Management Information Systems*, and *Journal of the Association of Information Systems*, are investigated. Given the subject's contemporary and technical nature, both peer-reviewed journals and conference proceedings are considered.

Figure 1 Data collection and analysis flow (see online version for colours)

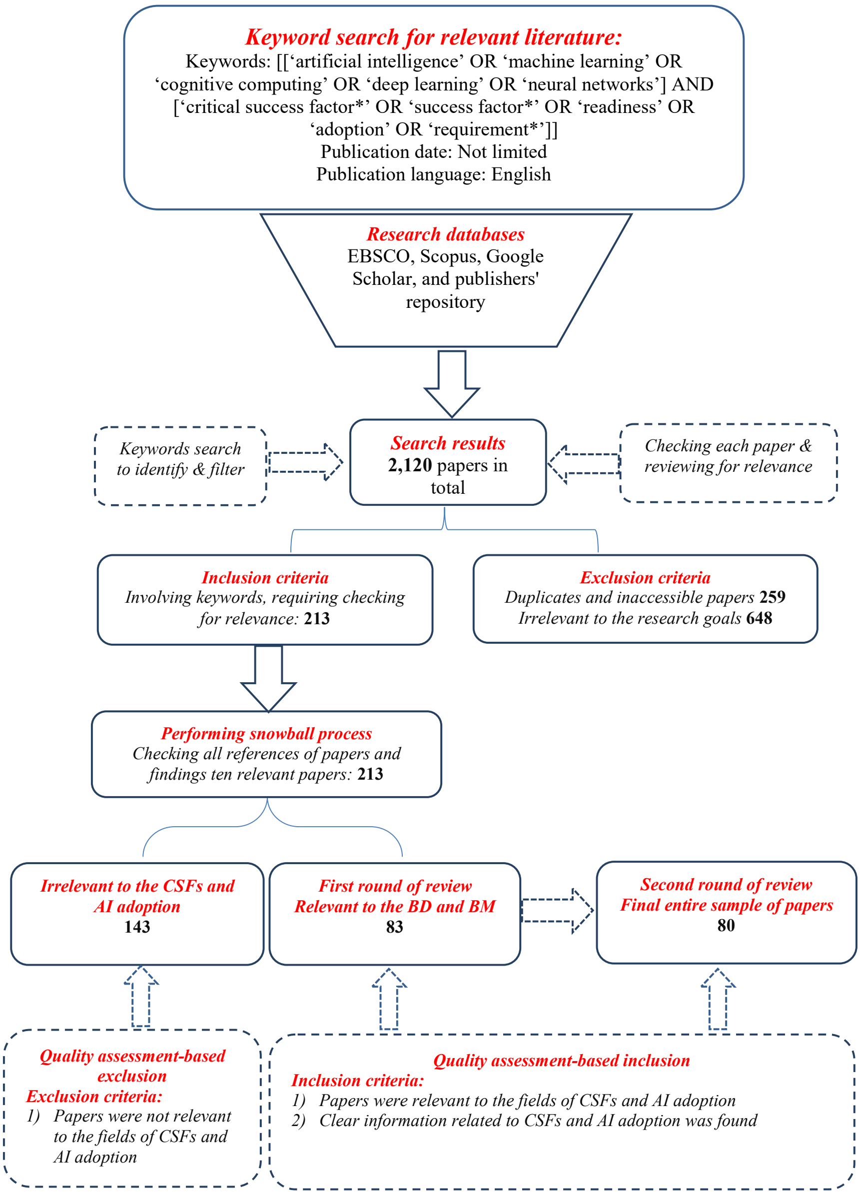


Table 1 The SLR process and outcome

Planning the review	Objective: identification of CSFs in the adoption of AI
	Scope: peer-reviewed journal articles and conference proceedings
	Search engine: EBSCO, Scopus, Google Scholar, and publishers' repository
	Language: English without restrictions regarding the year of publication
Conducting the review	Search terms [['artificial intelligence' OR 'machine learning' OR 'cognitive computing' OR 'deep learning' OR 'neural networks'] AND ['critical success factor*' OR 'success factor*' OR 'readiness' OR 'adoption' OR 'requirement*']] (2120 hits).
	Removing duplicates, not written in English, editorials, studies with no focus on AI, non-peer-reviewed scientific publications, and inaccessible articles led to an initial sample of 213 articles
	With snowball searching, 223 articles are added
	The 1st round of review of titles and abstracts (83 articles selected for a 2nd review round)
	The 2nd round of review: a full paper review (80 CSFs are identified)
Reporting the review	Structuring the identified CSFs
	Seeking consensus among authors striving for a 'collectively exhaustive and mutually exclusive' list of CSFs (leading to 32 distinctive CSFs)

The exclusion criteria were

1 inaccessible studies, (i.e., the articles where only an abstract was available)

2 not written in English

3 editorials

4 studies with no focus on AI

5 non-peer-reviewed scientific publications.

Once the inaccessible articles and duplicates are removed, the remaining articles are reviewed in two rounds. The review process is performed by three of the co-authors independently. First, titles and abstracts are screened, and the list of references is searched for promising new articles, (i.e., snowball searching); second, the entire article is reviewed. To structure the process of identifying CSFs, the technology-organisation-environment (TOE) framework is used, which provides a comprehensive structure to capture not only the technical aspects but also the 'soft' organisational, managerial, cultural, and environmental aspects of technology adoption at the firm level (Tornatzky and Fleischer, 1990). The review process resulted in a long list of CSFs across all three TOE dimensions; however, there were overlapping factors with slightly different labels and nuances. In achieving a set of collectively exhaustive and mutually exclusive CSFs, iterative discussions among authors took place. The review process led to a consensus on 32 distinctive CSFs.

2.2 Prioritisation of CSFs: AHP

While the SLR helped identify the CSFs, the prioritisation of the factors across the adoption stages could not be extracted from the literature. As discussed in the previous section, CSFs are inherently prioritised between competing factors that might impact adoption across various stages. Therefore, it can be considered a multi-criteria decision-making (MCDM) problem, where managers seek to evaluate and prioritise multiple criteria. MCDM enables determining the best alternative among various choices, possibly conflicting or correlated criteria (Sitorus et al., 2019). Generally speaking, there are three main types of MCDM, namely, value measurement models, outranking models, and reference-level models (Alharthi et al., 2015). In this study, a value measurement method, i.e., the AHP is adopted, which is one of the most commonly used MCDM methods (Fu et al., 2015; Latha and Suganthi, 2015). In the AHP method, explicit criteria are considered in prioritising and selecting alternatives. As such, the degree to which one decision option is preferred over another is represented by constructing and comparing numerical scores (Saaty, 2012). Value measurement models are widely used for prioritising CSFs for technology adoption processes (Salmeron and Herrero, 2005; Zaied et al., 2018), and AHP is among one of the most applicable methods among other quantitative ranking methods since it allows the researcher to easily measure the level of importance of each attribute compared to the others. Direct comparison between factors will enable individuals to calibrate the level of importance assigned to each factor (Alharthi et al., 2015).

In this study, the AHP provides a ranking of different criteria using weights obtained by pairwise comparison between CSFs (Nagpal et al., 2018). To select the most important CSFs as the inputs of the AHP technique, 33 experts from various industries participated. The sample size is comparable with similar studies based on AHP, e.g., Czekster et al. (2019) with 15 experts with a focus on ERP, and Nazari et al. (2018) with seven experts with an emphasis on decision support systems (DSS). Before the experts complete the related questionnaires, the primary purpose of the study, the definition of CSFs and the reasons for including CSFs at each stage of AI adoption are clearly explained. The majority of the respondents are from the finance industry (23%), followed by information technology (IT) (23%), retail (13%), energy (13%), and miscellaneous (e.g., pharma, telecom, aviation) with 19%. The respondents' role includes consultants both in consultancy firms and technology providers (52%), corporate agents such as solution architects, project managers, engineers (30%), and entrepreneurs in AI-driven companies (18%).

To prove the consistency of experts' opinions, the binomial test is applied to examine whether there are significant differences between experts' opinions. Therefore, the null hypothesis is 'There are no differences between experts' opinions'. Each expert states his/her opinion by selecting (1) as agree and (0) as disagree. The proportion test is assumed to equal 0.50, which means 50 per cent of experts are expected to agree on the proposed CSFs at each stage. The significance level of 0.05 is considered. Therefore, those CSFs with the agreed proportion of expert majority and significance value smaller than 0.05 are selected for prioritisation by AHP. For each pairwise comparison, experts were asked to rate the relative importance of criteria based on a nine-rank scale varying from equally important to extremely important. Also, each respondent's consistency ratio (CR) was calculated to ensure internal consistency (Wang et al., 2017). The results from all participants were aggregated to provide the final overall weights for each factor. Next, Friedman's non-parametric test for examining the difference between several related (ordinal) samples is used on the respondent's prioritisation. The participating AI experts were approached through the authors' contacts and the university network. The AHP survey is made accessible online with the BPMSG software (Goepel, 2018), and the results are tabulated and analysed in Microsoft Excel.

2.3 Refinement of CSFs: expert interview

The ranked CSFs were gathered from a long list of studies within various contexts; therefore, each CSF can be susceptible to a broad interpretation. To enhance the homogeneity of the selected and ranked CSFs, semi-structured interviews with AI experts were conducted (an overview of interview questions is provided in Appendix). The duration of the interviews was approximately one hour. All experts who participated in this research had at least three years of professional experience. The interviews aimed to collect experts' reflections and refinements of CSFs in the specific context of AI adoption. Semi-structured interviews help to open up complementary perspectives on a particular topic through the interviewees' mode of experience (Flick et al., 2004), and it is considered to be an effective approach in the mixed-methods studies where qualitative clarification of other methods' (often quantitative) output is needed (DeJonckheere and Vaughn, 2019).

In this section, the experts who participated in the previous steps were invited for an interview, from which 12 accepted the invitation. Although the sample size is not too extensive (more about the sample size in the discussion on limitations at the end of the article), it is not uncommon in the mixed-methods context (e.g., Kumar et al., 2021). The experts were requested to share their experiences and opinions regarding the ranked CSFs. Three of the authors of this study conducted the interviews, with one being the main interviewer, the second as the critical observer with complementary questions, and the third as a timekeeper who focused on overall structure and scope. All the interviews were transcribed (a total of 13 hours and 39 minutes of interview material). An AI-driven natural language processing (NLP) tool, Otter.ai, was used to transcribe the interviews (complemented with manual post-editing), and Quirkos 2.0 was used for coding the interviews. The results were tabulated in a Microsoft Excel database. Then, thematic coding of transcripts is applied to systematically extract patterns from the interviews (Rice and Ezzy, 1999). As such, the ranked CSFs were used as the 'master code', and the experts' refinements of the CSFs were added as nuance or subsets to each CSF. Once all the nuances were collected, the authors' started to identify the overlapping themes or patterns.

3 Results

The results of the three methods applied in this study are elaborated on next.

3.1 Identification of CSFs based on SLR

Based on SLR, a total of 32 CSFs from 70 sources are identified. The earliest publication on the CSFs in AI adoption dates back to 2015; however, there has been increasing attention ever since (see Figure 2). See Table 2 for a more detailed overview of the systematically reviewed publications.

Table 2 Detailed overview of CSFs based on SLR

		CSFs in AI	*Description*
Technology	User and product	Problem orientation	• Addressing users' problems (Fawkes and Lachut, 2018; Siddique, 2018; Pumplun et al., 2019; Van Esch and Black, 2020). • Adapting AI to the organisations' context (Fawkes and Lachut, 2018; Siddique, 2018; Pumplun et al., 2019). • Having a multidisciplinary approach to analyse the requirements (Yerlikaya and Erzurumlu, 2021).
		Explainability	• Following a transparent decision process (Lee and Shin, 2020; Møller et al., 2019). • Relying on an explainable algorithm and generating interpretable output (Lee and Shin, 2020; Møller et al., 2019).
		Customisation	• Identifying and analysing users' needs and conditions in different segments (Huang and Rust, 2018). • Presenting offers according to the segmented users and supporting them in the adoption process (Huang and Rust, 2018).
Organisation	Structure	Multidisciplinary organisational structure	• Changing organisational structure to ensure multidisciplinary collaboration where analytics and operations teams work together (Bughin et al., 2017a; Fountaine et al., 2019; Møller et al., 2019).
		Performance measurement	• Measuring business influences of AI using key performance indicators (KPIs) tailored to AI adoption (Bisson et al., 2018; Fountaine et al., 2019; Pumplun et al., 2019). • Linking AI to the business strategy (Bisson et al., 2018; Fountaine et al., 2019; Pumplun et al., 2019). • Adaption of AI with stakeholders' concerns (Fischer et al., 2021). • Improving the customer experience (Alsheibani et al., 2020b). • Improving business efficiency by identifying new ways of automating business (Alsheibani et al., 2020a, 2020b). • Monitoring performance for AI-enabled strategies (Yerlikaya and Erzurumlu, 2021).
		Data-driven decision-making	• Encouraging firms to adopt an 'AI orientation' in which data-driven decision-making is deeply rooted (Fountaine et al., 2019). • Replacing top-down decision-making and empowering teams on the front line (Fountaine et al., 2019). • Developing data-driven scenarios and intuitive perception ability (Yerlikaya and Erzurumlu, 2021; Li et al., 2017).
		AI and data executive at C-level	• Appointing a chief data officer (CDO) to send a clear signal about the business criticality of AI (Bisson et al., 2018). • Changing the way people look at data and ensuring that data becomes central to the business rather than being seen solely as an IT project (Tyler et al., 2016). • Establishing a data strategy, data management policy and aligning the data value chains (Tyler et al., 2016).
		Stakeholder involvement	• The transformative impact of AI business should be communicated to stakeholders, in particular, the internal employees, regarding employment and financially related concerns (Bughin et al., 2017a; Ng, 2018).
		Data governance	• Establishing overarching policies and procedures (Kask et al., 2019; Kolbjørnsrud et al., 2017; Yerlikaya and Erzurumlu, 2021; Janssen et al., 2020). • Ensuring ethical standards and values, data privacy and ownership (Kask et al., 2019; Kolbjørnsrud et al., 2017).

Table 2 Detailed overview of CSFs based on SLR (continued)

		CSFs in AI	*Description*
Organisation	Structure	Data governance	• Issuing open data policies (Yerlikaya and Erzurumlu, 2021). • Rolling-out planning on data connectivity and investments in computing (Yerlikaya and Erzurumlu, 2021). • Compatibility between data flow and logic and the structure of the organisation (Janssen et al., 2020). • Developing, planning and controlling approaches toward data management (Janssen et al., 2020). • Detecting changing patterns of data and algorithms (Janssen et al., 2020). • Collecting data at the source and ensuring the correctness, validity and usefulness of data (Janssen et al., 2020). • Developing self-organising and inter-organisational networks (Wang and Siau, 2018).
		Experimentation and iterative development	• Gaining experience through relentless iterations and rapid prototyping (Lee et al., 2019; Møller et al., 2019; Ng, 2018; Kolbjørnsrud et al., 2017). • Validated learning (Lee et al., 2019; Møller et al., 2019; Ng, 2018; Kolbjørnsrud et al., 2017). • Quick examinations by AI algorithms (Mayo et al., 2020). • Addressing challenges associated with AI development (Alsheibani et al., 2019). • Establishing an AI-driven ecosystem as an iterative process where scenarios are tested, and the best ones are implemented (Yerlikaya and Erzurumlu, 2021).
	Strategy	Build-or-buy decision	• A decision is required on whether to build AI technology and capabilities internally or source it out to external partners and vendors (Bughin et al., 2017b; Ringel et al., 2019; Skilton and Hovsepian, 2018). • Analysing the trade-off between being independent of external actors with full (technical) flexibility at the expense of (variable) scalability, cost and ease of use (Lee and Shin, 2020; Hosanagar and Saxena, 2017).
		Resource allocation	• Dedicating AI analytics budget with a long-term investment horizon (Bisson et al., 2018; O'Mahony et al., 2017; Pumplun et al., 2019). • Evaluating financial risks regarding the current context of challenges (Manta, 2020).
		Leverage existing competencies	• Encouraging firms to start from their strongholds with a clear link to the firm's strategy and vision, integrating into their existing operation, and leveraging the current knowledge base (Alsheibani et al., 2019; Bughin et al., 2017a, 2017b; Møller et al., 2019; Paschen et al., 2020a, 2020b).
		Business case orientation	• Following a clear business case (Bisson et al., 2018; Canhoto and Clear, 2020; Desouza et al., 2020; Alsheibani et al., 2019; Alsheibani et al., 2020a). • Initiating with small-scale problems (Bisson et al., 2018; Canhoto and Clear, 2020; Desouza et al., 2020). • Tackling large-scale business challenges (Bisson et al., 2018; Canhoto and Clear, 2020; Desouza et al., 2020). • Aligning AI transformation with existing strategies (Alsheibani et al., 2019; Alsheibani et al., 2020a, 2020b).

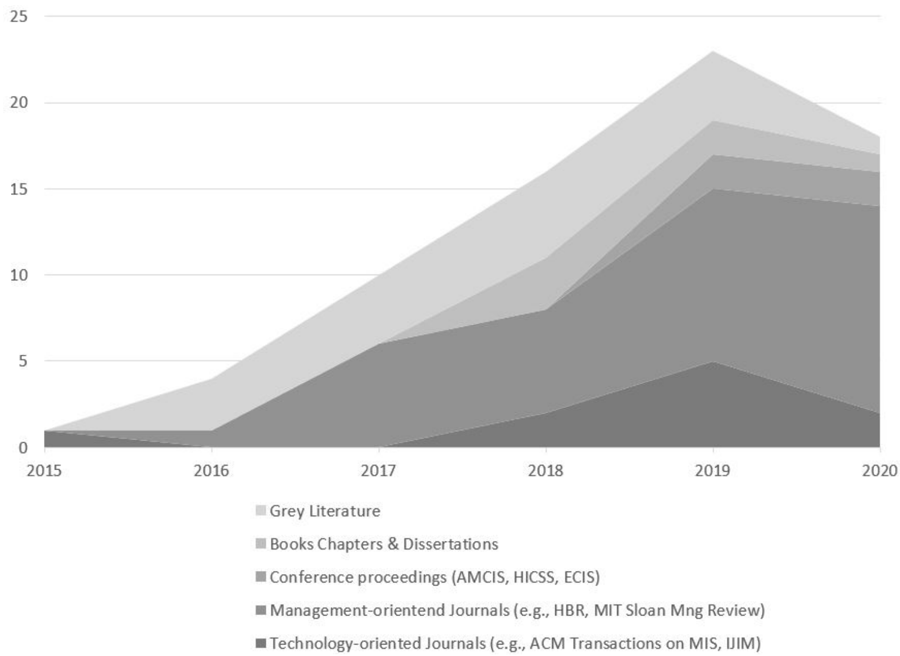
Table 2 Detailed overview of CSFs based on SLR (continued)

		CSFs in AI	*Description*
Organisation	Strategy	Business case orientation	• Developing a new business platform to power connected experiences for people and businesses (Alsheibani et al., 2020a; Alsheibani et al., 2020b).
		AI strategy	• Developing a holistic strategy to guide the transformation process (Bughin et al., 2017b; Swaminathan and Boston, 2019; Qvist-Sørensen, 2020).
			• Adopting AI strategy with experimentation and learning phases (Ng, 2018).
		Project portfolio	• Adopting a diversified project portfolio approach towards AI projects with a combination of quick-wins, larger, more complex, and valuable initiatives (Hosanagar and Saxena, 2017; Bughin et al., 2017b).
	Culture	Entrepreneurial culture	• Encouraging an entrepreneurial orientation (Dubey et al., 2020; Baldegger et al., 2020).
			• Sensing opportunities (Dubey et al., 2020; Baldegger et al., 2020; Khalid, 2020).
			• Discourage risk aversion as part of a pro-active, experimental, and innovative culture (Dubey et al., 2020; Baldegger et al., 2020; Khalid, 2020).
			• Having a positive attitude towards entrepreneurship (Khalid, 2020).
			• Quick decision-making capability (Khalid, 2020).
		Executive management support	• Understanding AI essentials (Butner and Ho, 2019).
			• Having a strategic AI perspective on its value-generating potentials (Butner and Ho, 2019; (Alsheibani et al., 2020a, 2020b).
			• Accepting a new data-driven way of decision-making (Thomas et al., 2016).
			• Having managerial skills associated with managing organisational adaptations to AI (Alsheibani et al., 2019).
			• Commitment of top-level leaders to new technology adoption (Alsheibani et al., 2019).
			• Supporting changes in behaviour, procedures, policies, and practices (Alsheibani et al., 2020).
			• Top management engagement (Alsheibani et al., 2020a; Alsheibani et al., 2020b).
			• Developing work teams with various skills (Alsheibani et al., 2020a; Persaud and Murphy, 2021).
			• Establishing authority and governance to allow AI technology to be embedded across business units and functions (Alsheibani et al., 2020a; Neubert and Montañez, 2020).
		Date-driven leadership	• Emphasising the role of AI-awareness, data-driven concepts, focusing on experimentation and creativity in AI adoption (Duan et al., 2019; Kolbjørnsrud et al., 2016a, 2016b; Yablonsky, 2019).
		Agile culture	• Adaptive firms, both at an individual and organisational level with AI issues (Brynjolfsson and Mcafee, 2017; Qvist-Sørensen, 2020; Ransbotham et al., 2017).
			• Adopting business processes and operations with AI (Delmolino and Whitehouse, 2018; Dogru and Keskin, 2020; Haenlein et al., 2019).

Table 2 Detailed overview of CSFs based on SLR (continued)

		CSFs in AI	Description
Organisation	Culture	Agile culture	• Adjusting AI to the market and technological trends and changing internal or external needs, with an accelerated adoption process (Brynjolfsson and Mcafee, 2017; Qvist-Sørensen, 2020; Ransbotham et al., 2017). • Encouraging firms to ensure lifelong learning and promote career flexibility (Delmolino and Whitehouse, 2018; Dogru and Keskin, 2020; Haenlein et al., 2019). • Developing a workforce with AI capabilities (Delmolino and Whitehouse, 2018; Dogru and Keskin, 2020; Haenlein et al., 2019).
	People	Entrepreneurial culture	• Encouraging an entrepreneurial orientation (Dubey et al., 2020; Baldegger et al., 2020). • Sensing opportunities (Dubey et al., 2020; Baldegger et al., 2020; Khalid, 2020). • Discourage risk-aversion as part of a pro-active, experimental and innovative culture (Dubey et al., 2020; Baldegger et al., 2020; Khalid, 2020). • Having a positive attitude towards entrepreneurship (Khalid, 2020). • Quick decision-making capability (Khalid, 2020).
		Change management	• Developing a change management strategy, which aims to overcome ‘algorithm aversion’ (De Cremer, 2019). • Encouraging employees to adapt to the new conditions (Fountaine et al., 2019; Jenke, 2018).
		Talent management	• Encouraging firms to establish centres of excellence to maintain consistency, reinforce learning and focus, create units and programs for talent attraction, and partner with recruiting companies to recruit talent and leverage internal human capital (Lee and Shin, 2020; Someh et al., 2020; Swaminathan and Boston, 2019). Recruitment should be scaled correctly; there is no need to frontload but, instead, hires slowly and steadily (Hosanagar and Saxena, 2017).
		Multidisciplinary collaboration	• Developing collective actions among a broad range of roles and practices, including business leaders, data scientists, software developers, statisticians, psychologists, marketers, operations teams, and legal advisors, where all technical, legal, market and domain expertise are combined (Agrawal et al., 2017; Ransbotham et al., 2017).
		Skills and training	• Making explicit learning and development strategy to familiarise everyone with AI improves company-wide ‘AI literacy’ (Agrawal et al., 2017; Kaplan and Haenlein, 2019; Møller et al., 2019).
Environment	Environment	Regulation and compliance	• Encouraging firms to consider laws, regulations, anti-discrimination, privacy, etc., throughout the design and implementation of AI solutions (Lee and Shin, 2018; Mogaji et al., 2021).
		Anticipatory regulations	• Monitoring continuously (Møller et al., 2019). • Dedicating role focused on the highly dynamic regulatory environment and its implications (Bisson et al., 2018). • Including social and societal influences (Fischer et al., 2021). • Government regulatory issues (Alsheibani et al., 2018). • To continually evaluate the changing AI landscape (Butner and Ho, 2019).

Figure 2 The trend of publications on 'CSFS in AI adoption' across various sources



3.2 Ranking of the CSFs with AHP

To select the CSFs across the three levels of adoption (i.e., exploration, implementation, scaling), the binomial test was applied, and experts were asked to select the most important CSFs in each phase by indicating their opinions (1) as 'agree' and (2) as 'disagree'. Only the CSFs selected by most experts at a 95% confidence level were considered for the ranking process. Accordingly, seven CSFs in the exploration phase, four in the implementation phase, and five in the scaling stage were chosen (see Table 3).

The AHP-based survey is filled out by 14 AI professionals from Europe, Africa, and Asia. A 7.2% of respondents have < 3 years, 42.8% between 3 to 7 years, and 50% > 7 years of experience in AI projects. The relative priority of each criterion is calculated through pairwise comparisons (the aggregated pairwise comparison matrix, CR, rank and weight of CSFs are presented in Table 3). It became clear that 'business case orientation' and 'executive management support' are the most important CSFs in the exploration phase, 'problem orientation' and 'data quality' are the most important CSFs in the implementation phase, and 'cybersecurity' and 'algorithm accuracy' are the most important ones in scaling stage. The CR is also presented as the respondents' internal consistency, which should be less than 0.1 for the judgments to be considered reliable (Saaty, 2012). The Friedman test indicates that the differences between the mean ranks of CSFs assigned by experts in the AHP section are significant (see Table 4).

Table 3 Aggregated pairwise matrices and prioritised CSFs in the AI adoption phases

	No	*Critical success factors*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*Weights*
Exploration	1	Problem orientation	1	1.215	1.794	0.653	0.992	0.928	0.583	0.128
	2	Data quality	0.822	1	1.379	0.431	1.018	0.827	0.460	0.104
	3	Entrepreneurial culture	0.557	0.724	1	0.337	0.752	0.490	0.357	0.074
	4	Executive management support	1.530	2.319	2.963	1	1.961	1.071	0.943	0.205
	5	Resource allocation	1.007	0.981	1.328	0.509	1	0.825	0.343	0.104
	6	Experimentation and iterative development	1.076	1.208	2.037	0.933	1.210	1	0.487	0.140
	7	Business case orientation	1.712	2.171	2.795	1.059	2.909	2.049	1	0.241
				Consistency ratio: 0.6%						
Implementation	1	Problem orientation	1	2.170	1.422	1.694				0.359
	2	Technology and system architecture	0.460	1	0.501	0.921				0.161
	3	Data quality	0.703	1.994	1	1.492				0.286
	4	Algorithm accuracy	0.590	1.085	0.670	1				
				Consistency ratio: 0.4%						
Scaling	1	Algorithm accuracy	1	0.831	1.237	1.101	1.883			0.222
	2	Cybersecurity	1.203	1	1.291	1.500	2.277			0.267
	3	Performance measurement	0.808	0.774	1	1.245	2.279			0.214
	4	Data governance	0.908	0.666	0.802	1	2.005			0.190
	5	Anticipatory regulations	0.530	0.439	0.438	0.498	1			0.105
				Consistency ratio: 0.4%						

Table 4 Friedman test results

Phase	*df*	*Chi²*	*Sig.*	*Mean rank*
Exploration	6	17.045	0.009	Business case orientation: 2.50
				Executive management support: 3.07
				Experiment and iterative development: 3.89
				Problem orientation: 4.11
				Resource allocation: 4.43
				Data quality: 4.61
				Entrepreneurial culture: 5.39
Implementation	3	8.188	0.042	Problem orientation: 1.82
				Data quality: 2.36
				Algorithm accuracy: 2.68
				Technology and system architecture: 3.14
Scaling	4	10.719	0.030	Cybersecurity: 2.32
				Algorithm accuracy: 2.64
				Performance measurement: 2.96
				Data governance: 3.93
				Anticipatory regulations: 4.14

3.3 Refinement of the CSFs in the context of adoption based on experts' interviews

The participants in the expert interviews were from different sectors, including retail, research, financial services, healthcare, food and beverage, all active as experts and senior advisors in AI for more than five years. Based on the experts' views, the ranked CSFs are refined. As a result, different actions and interpretations of each CSF seem to be at play. For instance, 'problem orientation' and 'data quality' are two CSFs in both the exploration and implementation phases. In the exploration phase, problem orientation is related to understanding users' and customers' needs, while in the implementation phase, it refers to identifying problems in deploying AI solutions. For instance, one of the interviewees stated, "AI is a mean to an end, not an end in itself. The objective is solving an issue – for example, saving money, increasing the top line or integrating more efficiency. We never start our exploration from the technology itself. We start from what is the problem that we are trying to solve". While another interviewee emphasised that 'while building our AI-enabled solution, our focus remains on 'deployability'; how else can we truly address our client's problems, whether that is an intelligent detection system or autonomous decision-making?' Data quality in the exploration phase is mainly about data cleaning and validity, while in the implementation phase, quality is primarily about data interpretability. For instance, one interviewee stated, "the starting point, even for organisations that are in an exploration phase, is that they already have business intelligence [BI] or analytics departments where the quality, quantity and availability [of data] is managed. In particular, data quality is critical, and it should represent a targeted population". Another interviewee underlines the importance of data quality within the implementation phase and states, "when you shake a tree hard enough, some fruit will fall off. But that says nothing about the quality of your yield. Data is useful only when we can turn it into insights that ultimately fulfil customers' need". See Figure 3 for the ranked and refined CSFs across the three stages of AI adoption.

Figure 3 An overview of refinements and nuances of CSFs from a TOE perspectives based on expert interviews (a full overview of quotes is available upon request)

Exploration

T **Problem Orientation**
- *Understanding users' and customers' tacit and explicit changing needs*
- *Adopting a solution orientation approach while heedful of the technological constraints*

T **Data Quality**
- *Preserving the data reliability and validity before classification*
- *Preserving integrity of data*

O **Executive Management Support**
- *Seeking compatibility between business model and AI solutions and requirements*
- *Establishing and supporting strategy with the AI solution*
- *Developing a holistic vision for the AI project*

O **Resource Allocation**
- *Allocating resources for AI without the pressure of expecting an immediate return on investment*

O **Experimentation and Iterative Development**
- *Initiating with incremental AI pilot studies*
- *Building feedback mechanism in the AI projects to improve the system gradually*
- *Promoting the spirit of continuous learning that underlies experimentation*

O **Entrepreneurial Culture**
- *Encouraging proactive explorative attitude*
- *Encouraging risk-taking with a vision*

O **Business Case Orientation**
- *Proposing and defining values for all stakeholders*
- *Proposing value assessment framework*

Implementation

T **Problem Orientation**
- *Identifying deployment and integration problems*
- *Exploring and selecting a feasible path for AI rollout*

T **Data Quality**
- *Preserving the interpretability and explainability of data analytics*

T **Algorithm Accuracy**
- *Developing algorithms with a focus on a macro level*
- *Evaluating multiple algorithms in parallel and selecting the one that yields the best performance*
- *Striving for algorithms compatible with changing conditions*
- *Seeking for algorithms with consistent performance*

T **Technology and System Architecture**
- *Providing open and scalable modular infrastructure*
- *Setting up system and enterprise architecture to preserve coherence between existing (legacy) systems and new AI solutions*

Scaling

T **Algorithm Accuracy**
- *Monitoring the outcome of algorithms and evaluate the existence/magnitude of biases*
- *Examining the accuracy of the proposed algorithms based on decisions-made*
- *Evaluate the maintainability of algorithms*

T **Cybersecurity**
- *Developing protocols regarding the security measures (e.g., data backup and recovery, network access and authorization, monitoring intrusion, update and patches)*

T **Performance Measurement**
- *Determining the Key Performance Indicators (KPIs) for evaluating the impact*
- *Quantifying the business impact*
- *Using dashboards to monitor KPIs seamlessly*

O **Data Governance**
- *Setting up standards and protocols to safeguard compliance, e.g., the GDPR requirements*

E **Anticipatory Regulations**
- *Following local regulatory changes*
- *Apply scenario analysis for future legislative acts*
- *Inclusive and collaborative (multi-stakeholder) risk mapping and mitigation*

4 Discussion and conclusions

Although the number of firms and industries experimenting with AI solutions is growing, AI adoption has been limited (Canhoto and Clear, 2020). There are repeated calls in the literature for more research on CSFs that accelerate or impede the adoption of AI (Herath and Mittal, 2022). CSFs are perceived as a simple and intuitive way to condense the complexities of modern management into a series of priorities (Chen et al., 2021a, 2021b). Following a mixed-methods approach, this study reviews a relatively large collection of IS publications based on which a vast array of technological, organisational and environmental CSFs is extracted. The CSFs are then shortened, ranked, and refined across the three phases of AI adoption, i.e., exploration, implementation, and scaling.

The empirical findings of this study hint that in the exploration phase, the organisational factors, such as 'business case orientation', 'executive management support', and 'promotion of entrepreneurial culture and experimentation', are the most relevant CSFs. This finding corroborates earlier studies on AI adoption, where the need for 'soft infrastructure' as the departure point is highlighted (Ammanath et al., 2020; Ng, 2020). It is noteworthy that cultural change is often less straightforward than setting the technology right because firms' contextual peculiarities and constraints need to be considered, leading to a unique change management journey (Bughin et al., 2017b). In stark contrast, within the implementation phase, the technological factors become more prominent, including 'pursuing a problem-oriented approach', 'safeguarding quality of data', 'ensuring algorithms' accuracy', and 'the adoption of technology and system architecture'. Although the role of technology and its relevance throughout the AI adoption process is not unanimously specified in the existing literature, it is considered a critical factor with an impact on adoption (Møller et al., 2019; Lee et al., 2019; Huang and Rust, 2018; Brock and Von Wangenheim, 2019). In the scaling phase, 'cybersecurity', 'algorithm accuracy', 'performance measurement', and 'data governance' appear to deserve a higher priority. Attention to cybersecurity, data governance, and focus on privacy have been emphasised by earlier studies (e.g., Alsheibani et al., 2018; Delmolino and Whitehouse, 2018; Siau and Wang, 2018; Singh et al., 2022). However, in this study, it became clear that the beforementioned factors became critical mainly in the last adoption phase.

4.1 Theoretical and managerial implications

Theoretically speaking, this study can be positioned within a growing community of scholars that is looking into the role of CSFs and AI, (e.g., Alhashmi et al., 2019; Alsheibani et al., 2018, 2019; Chen et al., 2021a, 2021b; Desouza et al., 2020; Dora et al., 2021; Mir et al., 2020; Pillai and Sivathanu, 2020) and provides the community with a comprehensive overview of CSFs relevant to AI adoption, as well as the variability of the CSFs' relevance across the adoption process. From a practical viewpoint, this study helps scholars and practitioners focus on a specific set of CSFs, enabling firms to develop more comprehensive policies, mobilise resources more efficiently, and build the capabilities needed for sustainable AI adoption more effectively.

4.2 Research limitations

As with any empirical study, the findings of this study must be viewed in light of some limitations. First, this study is the first attempt to triangulate various methods to provide a comprehensive view of CSFs; however, for a longitudinal understanding of firms' adoption process, qualitative case studies are more suitable. A more generic limitation is the sample size of the AHP-based survey and expert interviews. While the sample sizes correspond with the earlier studies (see Sections 2.2 and 2.3 for a more detailed discussion on sample size), a larger sample size can enhance the external validity of the finding. Therefore, the findings should be considered as a starting point for future studies as it explicates the areas that need further exploration.

4.3 Future research

Future research can evaluate the firms' maturity concerning the CSFs proposed in this study and qualitatively or quantitatively study how different levels of maturity impacts firms' performance, which, in turn, can trigger new series of research on how the transformation process can be managed to steer the firm towards a higher maturity level, (e.g., Ge et al., 2020), or exploring the adoption of specific AI applications, such as AI-driven forecasting, rather than AI as a generic technology (e.g., Ahmadi and Solaimani, 2021). Also, future studies can statistically examine the relationships between CSFs of AI adoption to determine the impact of factors on AI adoption. Furthermore, future studies can focus on developing and validating conceptual models with qualitative and quantitative methods such as interpretive structural modelling (ISM), path analysis and structural equation modelling (SEM) (e.g., Solaimani and Swaak, 2022) to categorise the variables and identify the most important factors while considering the correlation and interaction between CSFs.

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Appendix

Table A1 An overview of the semi-structured interview questions

Interview opening	What is your current role and organisation?
	What is your background, and what is your experience with AI technologies?
Artificial intelligence	What is the value of AI in your sector/area of expertise? Do you consider it as transformational? Why/why not?
	What is your view on the current adoption of AI in your industry/domain of expertise?
Phases of AI implementation	How relevant are the three indicated three phases of adoption? Are there any changes needed?
	How would you describe the phases of AI implementation in your industry/domain?
	What have you learned about each phase from your experience with AI projects?
CSFs for implementing AI	What are the CSFs for implementing AI in your industry/domain?
	[providing the interviewee with insights on CSFs derived from the literature review]
	Does this study capture relevant CSFs, and do they apply to your industry/domain? Are there any CSFs missing?
	Which CSFs would you rank as most important during each stage of the AI implementation and why?
	How do the discussed CSFs differ from other technologies (ERP, cloud computing, CRM), etc.)?
	Are the different clusters of success factors that could lead to a successful outcome?
Interview closing	Do you have any final thoughts about how to implement AI that we may have overlooked successfully?