Barriers to the Implementation of AI in Organizations: Findings from a Delphi Study

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Abstract

Artificial intelligence (AI), like many technological innovations before it, promises to revolutionize organizations. However, implementing AI in organizations is not as simple as it may appear. This exploratory research aims to unearth barriers to the implementation of AI in organizations. The methodology is based on a ranked-order Delphi study with 18 AI experts. By comparing our results with previous research on barriers to implementation of other information systems and to conceptual and practitioner literature on AI implementation, our findings underscore specific AI implementation challenges for organizations. Barriers to AI implementation fall under three main categories: (1) a lack of organizational capabilities related to data; (2) a lack of individual competencies related specifically to AI; and (3) generic implementation barriers previously observed in implementation research that persist with this innovation.

1. Introduction

Since its beginnings in the 1950s, artificial intelligence (AI) has been both promising and challenging for practice and in academia. Academic research on AI has advanced our understanding and ability to develop and use mathematical models [e.g. 1]. Recent practitioner interest in AI is fueled by these developments [2]. Enhanced analytical capabilities could translate into important benefits for organizations of all types [3]. In this study, we use a broad conceptualization of AI, as “the theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages” [4].

Our review of the literature highlights the fact that while AI can answer many questions and has the potential to solve many problems in organizations, successful implementation of AI is not guaranteed.

Gartner has noted recently that 85% of AI projects will fail to deliver on their promises [5], a failure rate that is considerably higher than that of IT implementation projects overall. An important step in understanding and encouraging the success of an implementation project is identifying the potential barriers to implementation [6]. Barriers interfere in some way with the overall success of the implementation of an innovation. They can be laws, rules, objects, practices, ideas, problems, structures, systems, practices or individuals that “prevent, inhibit, or discourage technology advancements” [7], p. 10.

The academic and practitioner literatures have provided conceptual suggestions for the low success rate of AI implementation. However, empirical validation of the nature of those barriers as well as their relative importance is currently lacking. Therefore, our research question is: *what are the barriers to the implementation of AI in organizations?* To answer this question, we conducted a ranked-type Delphi study [8] to unearth barriers to the implementation of AI, and to rank them by order of importance. Our work makes two important contributions. First, we provide an empirically derived ranked list of the most important barriers to the implementation of AI in organizations. Understanding the relative importance of each of the barriers is of interest to both academics and practitioners: the former to develop theories as to why certain issues inhibit AI implementation more than others; the latter to use these findings to better focus their efforts on overcoming these barriers. Second, our results contribute to outlining new organizational capabilities and individual competencies that are specific to AI and which affect its implementation in organizations.

The remainder of the paper is structured as follows. First, we review the literature on the implementation of IT and its associated barriers before we present an overview of artificial intelligence. Then, we present the details of the methods we used to conduct our Delphi study. This is followed by a presentation of findings followed by a discussion of our results. We conclude with limitations and suggestions for further research.

2. Literature Review

2.1 IT implementation and related barriers

The implementation of information technology (IT) is a multi-step process, starting with initial initiation discussions, and ending with infusion, or complete absorption of the system within the organization [9] and often requires important efforts to manage the organizational changes that accompany this process [10]. Academic and practitioner interest in IT implementation is fueled by the understanding that organizations can only realize benefits from technologies if they are implemented and used [11]. Yet despite ongoing research, the failure rate of implementation initiatives remains high [12].

One avenue for understanding the cause of this high rate of failure is an examination of barriers to IT implementation in organizations, as a reduction in the undesirable effects of these barriers is associated with greater success [6, 13] (for details of the literature review, please see the online appendix)[†]. Previous research has focused on IT implementation in general (for a comprehensive review of literature on the topic, see [13]), examined specific industries [e.g. 6] as well as specific IT [14-16]. The technology - organization - environment (TOE) framework has been found useful in past research to help classify barriers, or risk factors, to IT implementation (e.g. [17]). The TOE framework posits that adoption and implementation of innovations in organizations are influenced by contextual factors in three dimensions: the technology itself, the organization, and the environment in which it operates, and that these factors are interrelated [18].

To assess whether some barriers to IT implementation are enduring (1) over time and (2) regardless of the type of IT artifact involved, we examined three types of technologies spanning three different time periods: ERP [14], CRM [16] and cloud technology [15]. Our analysis reveals that weak organizational culture and lack of top management support are consistent across all three types of artifacts. Other common barriers included low levels of IT infrastructure to support the innovation, inability to perceive short and long-term benefits, unfavorable attitudes (for example employee resistance), the complexity of the implementation, and vendor related problems. In contrast, some of the barriers identified were specific to a given technology (e.g. low level of technological maturity was a barrier to cloud implementation; poor process engineering was a barrier to ERP implementation). For a complete list see Table 1. Therefore, we surmise that there is a possibility that, as a technological innovation

introduced within an organization, the implementation of AI may be associated with specific barriers.

2.2 Artificial intelligence

Artificial intelligence has been around since the 1950s [19] but recent advances in modeling techniques and computing power have uncovered opportunities to use AI in an organizational context [20]. AI has the potential to create value for organizations along the entire value chain, for example by optimizing research and development, and by improving demand prediction, business process management, customer targeting and customer experience [21]. However, because of many factors specific to AI, such as algorithmic opacity and dependence on quality data, organizations wanting to implement AI may encounter important barriers [22].

Literature on AI in computer science and engineering abounds; however, recent research has observed that there is a dearth of literature discussing AI from an IT and from a management perspective [23, 24]. Academic literature is beginning to address barriers to implementation of AI [25], although thus far these studies are conceptual and not grounded in empirical data. Practitioner literature on the topic identifies both general barriers to IT implementation as well as others that are specific to AI. For instance, suggested barriers specific to AI include insufficient quantity and quality of data [22, 26]; inability to identify a clear use case [20, 26], and issues related to ethics, governance of data and governance of AI [25].

The barriers culled from extant literature are summarized in Table 1 and have been categorized by the authors based on the TOE framework. [18]. Our review of the literature uncovered two important gaps: the lack of empirically identified barriers to the implementation of AI; and the relative importance of these barriers for practitioners. The present study contributes to address both gaps.

3. Methodology

Understanding what barriers may be preventing the successful implementation of AI in organizations will help managers better prepare when planning these projects and will provide researchers with a clearer understanding of what may distinguish these projects from other more typical implementations. As this topic has received little empirical attention, our research question is exploratory in nature, and therefore a ranking-type Delphi study is an appropriate method [27, 28]. Delphi methods combine the collection of input from a group of experts on a specific topic and

consensus-building among these experts. Ranking-type Delphi methods seek to build consensus among experts in a given field on the relative importance of a set of issues [8]. As the validity of the results of a ranking-type Delphi study depend on the rigor of the research

design and execution, we followed the guidelines provided by Paré et al. [8] during all phases of the study. In addition, we respected the three overarching criteria for Delphi studies: anonymity of participants; controlled feedback; and aggregation of responses [29].

Table 1. Summary of literature review on barriers to implementation

TOE	Barriers	Gen.	Technology- Specific				
			ERP	CRM	Cloud	AI -A	AI- P
Environ- ment	High cost of IT implementations	X	X			X	X
	Low level of technology maturity				X		X
	Rapid evolution of technological innovations	X					
	Ethics issues					X	
Organization	Inadequate training	X	X				
	Lack of sufficient systems for measurement			X			
	Absence of process engineering		X				
	Inappropriate organizational structure	X					
	Weak organizational culture (limited use of best practices, lack of communication and coordination, political factors, organizational change)	X	X	X	X	X	
	Ambiguous strategic vision		X			X	X
	Inability to perceive short-term and long-term benefits of IT (lack of awareness and knowledge about IT, anticipation of lower ROI on IT expenses, lack of leadership, insufficient IT policies)	X		X	X	X	X
	Lack of understanding of what AI is (benefits and use)						X
	Unfavorable attitude (reticence of adopting new technologies, technology is perceived as a threat, resistance to change, feeling of lacking time)	X	X	X		X	X
	Poor identification of clear use cases					X	X
	Insufficient quantity of available data					X	X
	Lack of technical expertise (lack of trained employees with required skills, lack of competence and confidence to implement the right technologies)	X	X	X		X	X
	Vendor-related problems (selection of IT product among multiple vendors, contracts, maintenance, upgrades)	X	X		X		X
	Governance issues					X	X
	Lack of end-user engagement	X					
	Lack of engagement of leadership (IT is not integrated in organizational strategy, lack of alignment between business and IT objectives, limited spending, budgeting problems)	X	X	X	X	X	X
	Responsibility and accountability issues					X	X
	Underperformance of the project team		X				
Org/ tech	Complexity of implementation (system integration, poor interoperability between applications, incompatibility with existing systems)	X		X	X	X	X
Technology	Low data quality within the organization			X		X	X
	Low level of IT infrastructure (limited bandwidth, inadequate technology and systems, poor telecommunications structure, lack of computing equipment, insufficient resources)	X	X		X	X	X
	Concerns about security and confidentiality	X			X	X	X
	Technical problems		X				

Legend: AI-A = Academic literature on AI; AI-P = Practitioner literature on AI

The Delphi study described in this paper followed four main phases: (1) selection of panelists; (2) issue identification; (3) issue validation and refinement; and (4) issue ranking. Each phase is detailed below. The study was conducted from October to December 2019.

3.1 Phase 1: Selection of panelists

A critical step in a Delphi study is the selection of the group of experts [30], called the panel. Our inclusion criteria for panelists was that they were professionals in the field of AI, with knowledge and experience of implementation of AI projects, as well as knowledge and experience in IT. As AI has only recently been widely adopted, a minimum of two years of experience in AI implementation projects was judged sufficient to be included in the panel. One of the strengths of a Delphi study is the diversity of its respondents [8], therefore potential panelists included project managers, consultants, solutions providers and research professionals working in a variety of sectors including aerospace, energy, manufacturing, insurance, as well as consulting. Paré et al. [8] recommend between 14 and 30 panelists; our panel began with 26 panelists, with 18 completing all rounds of the study.

Convenience sampling, followed by snowball sampling, [31] was employed to identify potential panelists for this study. In collaboration with a leading North American institute that aims to bridge the gap between AI professionals and academics, we identified and contacted several potential panelists. The professional network LinkedIn was also searched using keywords AI and “machine learning” and professionals were contacted based on the extent and appropriateness of their background. Finally, the third author recommended several personal contacts. In addition, all potential panelists were asked to refer other individuals who fit the criteria. Panelists were from France and Quebec, Canada, two academic and industry AI hubs. In total, 41 panelists were invited, 26 of whom agreed to participate in the study (response rate of 63%). 18 completed all phases of the study (final response rate of 44%). Demographic details of the panelists can be found in Table 2; full descriptions are available from the second author. To thank them for their participation, panelists were provided with the compiled results, and an opportunity to meet with the first author to discuss the results.

General measures were taken to minimize panelist attrition, which can be expected due to the fact that Delphi studies occur over the course of several weeks, including sending frequent reminders during each phase, and ensuring data were aggregated rapidly between phases [28]. To maintain the anonymity of respondents—a key characteristic of Delphi studies

[29]—responses were aggregated and did not include identifying information before being shared with panelists in subsequent rounds.

Table 2. Profile of panelists

		Initial sample		Final sample	
		n	%	n	%
Gend.	Male	23	88%	17	94%
	Female	3	12%	1	6%
Age	< 30	8	31%	4	22%
	30 - 39	5	19%	2	11%
	40 - 49	5	19%	5	28%
	50 - 59	4	15%	4	22%
	> 59	4	15%	3	17%
Educ.	College	1	4%	1	6%
	Undergr.	7	27%	6	33%
	Master's	15	58%	10	56%
	MBA	3	11%	1	6%
Experience		Mean	Median	Mean	Median
Prof. exp. in IT (yrs)		16.5	15	18.6	21
Prof. exp. in AI (yrs)		5.8	3	4.7	3

3.2 Phases 2 and 3: Identification and validation of issues

The second phase involved the identification of barriers [8]. Following Schmidt et al. [32] we solicited input from the panelists both for the development of the list and for the ranking of the barriers. Panelists were not provided with a preliminary list, such as the one that resulted from the literature review, when asked to provide barriers. They were given three weeks to list all barriers that could arise when implementing AI in organizations based on their experience, and to include descriptions or definitions for each. We used Qualtrics (<https://qualtrics.com>) to administer all communication with panelists, which enabled us to track their participation throughout the study as well as to ensure anonymity. A total of 117 barriers were initially identified. The first and third authors consolidated the list of identified barriers and clarified the descriptions provided by the panelists. After consolidation, the list included 17 barriers.

In the third phase, this consolidated list of barriers and their respective descriptions was sent to the panelists for validation. Following the panelists' input, certain items were combined, refined, removed, and added, for a final list of 16 validated barriers.

3.3 Phase 4: Ranking

The final phase involved two rounds of ranking. The objective of this phase was to obtain consensus between the panelists on the relative importance of each of the barriers. As a first step, participants were provided with a randomized list of the identified barriers and asked to rank them in order of importance (from 1 to 16, 1 being the *most* important). Importance was defined as the severity of the impacts or consequences associated with each barrier during implementation in an organization. 22 panelists responded in this round. Consensus of ranking is measured using Kendall's coefficient of concordance, or W [32]. A W of 0.7 or above is considered high; 0.5 is considered medium, and 0.3 or below is considered low. After the first round of ranking, Kendall's W was 0.262, or low. Participants were therefore contacted a second time, provided with the initial ranking, and asked to re-rank the barriers considering the overall results. After the second round of ranking, for which 18 panelists provided responses, Kendall's W was 0.432, a slight improvement, but still somewhat low.

Paré et al. [8] propose three "stopping rules" to determine if further rounds of ranking should be conducted: a W of over 0.7 was achieved; three rounds of ranking have been conducted; and the absence of significant difference between the results of two successive rounds. As the first two conditions were not satisfied, a test of the difference between the two lists was conducted. A Wilcoxon signed ranking test was considered appropriate to determine statistical difference between the two lists as both lists were comprised of the same population, and as the data points were not binary [17, 33]. Only the responses of the 18 panelists who provided lists in both rounds were compared, as this test is based on paired samples. This analysis revealed that only two items differed significantly between the two tests, indicating that further rounds of ranking would likely not change the results.

To confirm this conclusion, a clustering exercise was performed [17]. A hierarchical ascending classification method with a Gower distance computation was used, leading to a four-cluster solution that was deemed optimal based on examination of the resulting dendrogram. An examination of each cluster revealed the presence of a majority solution [17]: cluster 1 contained 11 of 18 panelists, with a W of 0.690. A W of lower than 0.7 is still considered strong when there are more than 10 participants [32]. Kendall's W for each other group was moderate to high; therefore, it was considered appropriate to stop the ranking after two rounds [8, 17].

4. Results

Because we asked panelists to identify barriers on their own, the resulting list of barriers is entirely based on the judgments of the experts. Table 3 lists the barriers identified by panelists along with their final rankings. Of note is the fact that identical or similar barriers to most of those identified by the panel had been mentioned previously in either academic or practitioner literature, with the notable exception of a lack of skills for the industrialization of AI. This barrier was considered distinct from a lack of availability of talent, which, according to the panelists, referred specifically to data engineers and data scientists, whereas industrialization required different skills. Several of the barriers identified were not mentioned in literature on implementation in general and were therefore considered specific to AI.

Table 4 presents the ranked list of barriers overall, and by cluster. An analysis of the panelists (demographics, education, experience, and industry) revealed no statistically significant differences between the clusters; however, panelists in cluster 2 had the fewest years of experience with AI in general.

Delphi studies enable the measurement of consensus between participants, as well as where participants do not agree. In terms of consensus, one of the two barriers that appeared in the top five in all clusters is specific to AI: low understanding of the business potential of AI. Lack of quality data and low volume of available data, barriers that are perhaps not specific to AI but have major implications for the creation and use of AI models, consistently appeared in the top 10, as did lack of available talent, or data scientists and engineers able to manage the data and create models.

Four barriers stood out as being consistently ranked low. These were considered sufficiently important to make the list of barriers, but they did not seem to stand out for participants as being the most important. Two of these barriers are common across all types of IT implementation (IT infrastructure issues; change management issues), and two were specific to AI (immaturity of the legal environment; ethical issues).

Four barriers received a low level of consensus (gap of more than eight levels between groups): lack of top management support, lack of strategic vision, lack of skills for industrialization and low volume of available data. Of these four, only the last two are related specifically to AI.

Table 3. Barriers to AI implementation identified by panelists, in alphabetical order

Barrier	Description	In lit. search		
		I	AI A	AI P
Change management issues	Poor planning of the change management activities that must accompany the implementation of AI limits the nature and the extent of the benefits organizations can realize from these initiatives.	X	X	X
Data governance issues	A lack of data governance maturity complexifies the management of data protection, data accessibility and the data life cycle.			X
Ethical issues	Ethical issues related to the use of AI slow its implementation in organizations.		X	
Immaturity of the legal environment	In some countries, a lack of clear regulation of the use of AI slows its implementation in organizations.		X	
Insufficient availability of talent	The difficulty of finding employees with the required skills for AI both internally and externally slows the implementation of AI in organizations.	X	X	X
IT infrastructure issues	The IT infrastructure of the organization is not ready to support the realization of AI projects (IT infrastructure in general, but also integration of technologies that would be used to build and deploy models with existing organizational systems, etc.).	X	X	X
Lack of quality data	A lack of high-quality data - i.e. data that is sufficiently precise, objective, and reliable - has a negative impact on the creation of high-quality models.	X	X	X
Lack of skills for industrialization	The lack of internal expertise to facilitate industrialization and operationalization of AI slows its implementation in organizations			
Lack of strategic vision	A lack of strategic vision consists of a difficulty to select the right AI projects which would improve business processes and generate value for the organization.	X	X	X
Lack of top management support	A lack of top management support has a negative impact on the speed with which decisions are made and the priority given to the deployment of AI in an organization.	X	X	X
Lack of understanding of the business potential of AI	The true potential business value of AI, as well as its limitations, remain difficult for managers to grasp.		X	X
Lack of understanding of the technical aspects of AI	Limited knowledge of the technical aspects of AI, such as the methods and models that could potentially be useful in a given context, slows the implementation of AI in organizations.		X	X
Low volume of available data	Insufficient data limits the organization's ability to create high quality models.	X	X	X
Resistance to change	The lack of knowledge and education about the implications of the implementation of AI for employees are a cause of resistance to its implementation in organizations.	X	X	X
Security and confidentiality risks	The risk related to the security and confidentiality of data and the models used by AI.	X	X	X
Uncertain return on investment	The uncertainties connected to a return on investment as well as the timeline necessary for the implementation of AI in an organization are risk factors that are difficult to manage.	X	X	X
Legend: I = Implementation literature; AI-A = Academic literature on AI; AI-P = Practitioner literature on AI				

5. Discussion: Implications of the novelty of AI

Although AI has been around for over 60 years, now that organizations are taking a broader interest in its adoption, industrialization poses specific challenges. As evidence of these challenges, many of the barriers to the implementation of AI are different from other

types of implementation. While all definitions provided by the panelists describe barriers in the context of implementation of AI, six of the barriers (37%) did not appear in previous IT implementation studies. This finding is consistent with previous research that indicates that AI poses significant new challenges for organizations [22]. The barriers identified cover the entire spectrum of contextual factors [18] but most are related to organizational capabilities and individual

competencies linked to the technology, demonstrating the interconnectedness of these two types of factors for the implementation of AI. Generic, recurring barriers also have specific implications when the technology being implemented is AI.

Table 4. Results of ranking of barriers

Barriers	All	Ranking by cluster* (difference)		
		1	2	3
Lack of understanding of the bus. pot. of AI	1	3 (-2)	3 (-2)	3 (-2)
Lack of quality data	2	4 (-2)	2	5 (-3)
Lack of top mgmt. support	3	2 (+1)	13 (-10)	1 (+2)
Lack of strategic vision	4	1 (+3)	16 (-12)	4
Insufficient availability of talent	5	8 (-3)	5	6 (-1)
Uncertain return on investment	6	9 (-3)	4 (+2)	2 (+4)
Lack of skills for industrialization	7	5 (+2)	8 (-1)	16 (-9)
Lack of understanding of the tech. aspects of AI	8	6 (+2)	6 (+2)	11 (-3)
Low volume of available data	9	10 (-1)	1 (+8)	9
Data governance issues	10	7 (+3)	14 (-4)	10
Resistance to change	11	11	7 (+4)	8 (+3)
Security and confidentiality risks	12	13 (-1)	9 (+3)	7 (+5)
IT infrastructure issues	13	12 (+1)	12 (+1)	12 (+1)
Change management issues	14	14	10 (+4)	13 (+1)
Immaturity of the legal environment	15	16 (-1)	11 (+5)	15
Ethical issues	16	15 (+1)	15 (+1)	14 (-2)
Overall W=0.432; Cluster 1 (11 members) W=0.690; Cluster 2 (3 members) W=0.548 Cluster 3 (3 members) W=0.648 *Cluster 4 had only 1 member				

5.1 New data-related organizational capabilities

Many of the barriers mentioned by our panelists were related to data, an integral part of ensuring that AI algorithms can learn and make predictions [34]. While other studies have suggested the importance of data for AI, this study highlights in what ways data impacts implementation of AI in organizations. Our panelists highlighted two specific capabilities (data acquisition and data governance) that when lacking, create barriers. First, under the resource-based view of the firm, data, as input for AI models, is considered a resource for firms. Firms must ensure that the data they acquire is of sufficient quantity and quality for AI to

meet organizational goals. As our panelists consistently noted data quality and quantity as barriers to implementation, it appears as though some organizations may be unable to reach these thresholds. For all clusters of panelists, data quality was more important than quantity. The concept of data quality has been discussed at length [35] and the results of the present study demonstrate that organizations still struggle with ensuring data is of sufficiently high quality. Insufficient volume of data was also a barrier to implementation, albeit not as important as insufficient quality. This is consistent with previous research that notes that the amount of data alone is not what makes it a “big deal,” but rather how the data can be of value for an organization [36]. Interestingly, cluster 2 ranked data quantity much higher than the other clusters. Upon further examination, the panelists in this cluster had the lowest length of experience with AI. Constructivist learning theories posit that knowledge is built on experience [37] and may explain why panelists with the least experience tended to rank data quantity higher in importance than did those who had more experience.

Beyond data acquisition, our panelists noted that a lack of data governance is a significant barrier to implementation of AI. Data governance refers to “the overall management of the availability, usability, integrity, and security of data” [36] (p. 403). According to our panelists, a lack of organizational policies that determine how data is accessed, used, and protected throughout the data life cycle is hindering the implementation of AI. This is consistent with previous research suggesting that data governance influences an organization’s ability to generate value from data [36].

Furthermore, our panelists indicated that the maturity of the legal environment with respect to AI, an environmental factor [18], influences the ease of implementation. These regulations are shaped in part by the broader normative force of digital ethics [38] which may also be at different stages of maturity. Moreover, our panelists clearly indicated that the maturity of the legal environment was a different barrier than ethical issues. This is consistent with Floridi [38], who notes that digital regulation, along with digital ethics, shape digital governance in organizations, emphasizing the separateness yet interrelatedness of these three concepts. Ethical issues were also included as a barrier by our panelists. Organizations likely must be able to respond to these environmental barriers to successfully implement AI.

Interestingly, legal environment maturity was consistently ranked in the bottom five by our panelists. In a follow up interview, one of our panelists noted the differences in maturity between different environments, namely Europe and the Canadian

province of Quebec, stating that companies adapt their AI strategies to the existence or absence of clear regulations. Previous research has highlighted the importance of clarifying the legal status of AI to reduce uncertainty, and to determine responsibility if something goes wrong [25, 39]. Several of our respondents were either currently working or had previously worked for European organizations, where regulations are more established than in Canada. While they recognized how the immaturity of the legal environment could create barriers to implementation, for many it was not an important issue.

5.2 New AI related competencies

At the leadership level, a lack of understanding of AI on the part of management creates barriers to AI implementation. Our respondents differentiated between a lack of understanding of the technical aspects of AI and of the business potential of AI as separate barriers, with a lack of understanding of the business potential of AI being the highest ranked barrier by our respondents. This is consistent with previous research that notes that seeing the potential value of big data is elusive for many incumbent organizations and affects their implementation of big data technologies [40]. While understanding the connections between these barriers was not the objective of the present study, previous research suggests that this barrier is fueled in part by a lack of understanding of the technical aspects of AI [20].

Consistent with our panelists' observations, many managers in companies that lag in adoption of AI have indicated that they only have a basic understanding of how AI works [20]. Ransbotham et al. [20] recommend that, rather than assuming they can absorb an understanding from exposure to the industry through site visits to high-tech firms, managers take introductory courses in AI to understand its basic workings. In a broad sense, when business leaders understand a particular innovation and the benefits it can provide for an organization, the implementation of the innovation is more successful [41], and AI appears not to be an exception.

AI implementation also requires specific individual technical competencies. Data preparation and model building require the skills of data engineers and data scientists, respectively. This talent is currently in insufficient supply, according to our panelists. These are two key roles in the AI development process, and the rapid growth in the field is accompanied by an increase in the number of experts and specialists in these fields [25]. However, the current talent pool possessing these skills has not grown as rapidly as the demand, and therefore has not been able to meet the

surge in organizational interest in AI implementation [20, 25, 42]. To overcome this project-level barrier, three pathways have been suggested: specialized recruitment tactics, on-the-job training, and investment in AI research centers [20, 42].

Beyond data preparation and model building, specific skills are needed for the industrialization of AI. Our panelists emphasized that a lack of experience in industrialization of AI, or the ability to insert AI into everyday organizational processes, is a barrier to AI implementation that is different from lack of talent for data preparation and model building. This barrier did not appear in our literature search yet was ranked in the top 10 barriers by most of our respondents, reflecting its relative importance. Because they require different skills, AI in the lab and AI deployed in organizations seem to be different processes [43]. Practitioner literature proposes the creation of a new role, "machine learning engineer," to address this specific barrier [44].

5.3 General implementation barriers that remain for AI implementation

Of the 16 barriers identified by our experts, six were general barriers to implementation that have been repeatedly mentioned in the literature. Not surprisingly, lack of top management support and lack of strategic vision were among the top five barriers overall to AI implementation. Top management support has long been considered essential for successful IT implementation [13, 41, 45]. Lack of top management support for AI can manifest in limited spending on AI projects and lack of integration of AI projects into the organization's business strategy [26], particularly in firms where adoption of these technologies implies substantial change in organizational processes [40] and is most frequently observable in organizations that have a passive orientation towards AI [20]. A lack of strategic vision for AI refers to an inability to see where and how AI can bring value to an organization. Vision clarity has been found to be a significant determinant for readiness for change in other types of IT implementation, and to be linked to successful change management [46], suggesting that a lack of a clear strategic vision may also be influencing resistance to change, another barrier identified by our respondents.

6. Conclusion

This study has empirically identified barriers to the implementation of AI in organizations. Our results show that many of these barriers are unique and specific to AI, including a lack of management

understanding of the business potential and technical aspects of AI, a lack of expertise for building algorithms and for industrializing AI. This study has also demonstrated how the nature of AI, particularly its dependence on data, creates barriers specific to its implementation, such as issues related to data quality, data quantity and data governance.

The practical implications of the findings are twofold. First, this study emphasizes the importance of management understanding of AI for successful organizational implementation. Second, it demonstrates the broad array of new organizational capabilities and individual competencies that, when lacking, impede the implementation of AI in organizations. To address this, organizations may want to look beyond data science and data engineering to the required skills for industrialization of AI.

This study is not without limitations. First, the nature of the Delphi method means that we relied on limited input from experts. However, we ensured that the study was conducted with rigor to obtain the most reliable data possible. Second, we did not achieve a high rate of consensus among all panelists. However, as the nature of our object of interest is highly dynamic and the panelists were very diverse, the level of consensus obtained can still be considered satisfactory, and majority agreement allows for some insights.

Future work in this area could include further study of how the identified barriers matter over time or are related with one another, particularly how a lack of understanding of AI impacts further barriers. Previous literature suggests how some of the barriers are interrelated (e.g. [38]) and how they can be overcome (e.g. [20, 42]), and future research could test these suggestions.

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Online Appendix

† The appendix detailing our literature review strategy and summarizing the findings of the literature review is available online at <https://bit.ly/3j9eUS4>.