Unmasking Biases and Mapping the Landscape of AI Adoption in Diverse Business Functions Through a Delphi Study

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Artificial Intelligence (AI) tools are exceedingly being introduced in various business sectors as a way to improve efficiency and drive overall organisational performance. Prior research has uncovered many success and failure factors influencing the adoption of these tools. However, in the absence of a common understanding between practitioners and researchers, factors deemed theoretically significant do not always align with reality, resulting in a researcher bias in AI adoption literature. Additionally, these factors and their priorities depend on specific business functions, deeming existing one-size-fits-all AI adoption theories incapable of explaining these nuances. To address these shortcomings, this study investigates the existence of a potential researcher bias and establishes factors influencing AI adoption in different business functions through a 2-fold, 3-round, 3-panel Delphi study. The findings establish a potential researcher bias and confirm that factors influencing adoption, and their priorities, differ by business functions. This study contributes to literature by first establishing the potential researcher bias and then furthering the understanding of factors influencing adoption for different business contexts. In a pivotal contribution to practice, this study enables organisations to foster better adoption practices based on different business functions.

Keywords:
artificial intelligence (AI), adoption of AI, delphi study, AI-driven organisations, AI-driven innovation, AI-driven marketing, HR and finance

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1 Introduction

Artificial Intelligence (AI) is revolutionising the way organisations function in different business sectors. In the form of business tools, this technology has permeated several domains like manufacturing (Li et al., 2017), hospitality (Nam et al., 2021; Price, 2019), finance (Ahmed et al., 2022; Bahrammirzaee, 2010), marketing (Chintalapati & Pandey, 2022; Davenport et al., 2020; Wierenga, 2010), and administration (Brougham & Haar, 2018; Kolbjørnsrud et al., 2016). For example, analysts at the McKinsey Global Institute estimate that 56 percent of typical "hire-to-retire" tasks could be automated using machine learning and cognitive agents (Bustamante & Gandhi, 2018).

Related research suggests various factors that lead to successful AI adoption in workplaces, such as trust (Bedué & Fritzsche, 2021), technology readiness (Brock & Khan, 2017; Janssen et al., 2020), top management support (Duan et al., 2017; Kurup & Gupta, 2022; Saberi et al., 2019; Yang et al., 2015) and explainability (Lee & Shin, 2020; Solaimani et al., 2023). Though the various advantages of using AI technology at work are established, there exist several challenges to its adoption in the workplace like limited understanding of the technology (Nam et al., 2021; Volkmar, 2020; Zerfass et al., 2020), lack of skilled personnel (Hair Jr. & Sarstedt, 2021; Zerfass et al., 2020), implementation issues (Kolbjørnsrud et al., 2016; Nam et al., 2021) and technological inadequacies (Jarek & Mazurek, 2019; Wierenga, 2010).

Such insights into the success and failure factors are usually gained by researchers who study how professionals use AI tools in the workplace. Hence, the findings are the result of an interpretation phase by the researchers who analyse data based on their own experiences, values, opinions, and knowledge (Chenail, 2016; Miyazaki & Taylor, 2008; Romano et al., 2021). This can bias the inquiry, misinterpret the results and reduce the trustworthiness of research (Chenail, 2016). Moreover, researchers may be unfamiliar with AI tools and may potentially infuse biases either in the data collection or the analysis stage (Romano et al., 2020). Potential biases among researchers could also be exacerbated by the popular AI narrative perpetuated in the general media (Ouchchy et al., 2020), even though training in the scientific method should lower this influence (Chenail, 2016).

When a researcher bias exists, subsequent findings may not be in line with the views practitioners hold, posing a problem for the development of theory that sufficiently reflects reality. It could mean that a developed theory cannot adequately explain the real world. While there exists research on the success and failure factors on AI adoption, we are not aware of studies that investigate if researchers and practitioners share a similar view on success and failure factors. If both populations share a similar view, current research will not suffer from the consequences of a researcher bias. However, if researchers and practitioners have different views, then a potential research bias may be a threat to theory development on AI adoption. Therefore, this study investigates the following research question, *"How do practitioners and researchers differ in their views on the success and failure factors of adoption of AI-based tools?"*

Additionally, factors influencing adoption can vary across different business functions. However, current research on AI adoption often builds on general theories such as Diffusion of Innovation (DOI), Unified Theory of Acceptance and Use of Technology (UTAUT) and Technology, Organisation and Environment (TOE) (Radhakrishnan & Chattopadhyay, 2020), that are domain-independent. We posit that distinct factors influence the adoption of AI tools in different business functions. For example, efficiency and scalability may be the priorities for AI tools aiding in organisational management, while creativity and experimentation may be important for AI used to aid innovation, whereas personalisation and trainability may be more important for the core business domains of marketing, finance and HR. This phenomenon remains largely unaddressed in current literature, leading to our second research question, "*What are the distinct sets of factors influencing AI adoption across diverse business functions, and how do they vary in their prioritisation?*"

To answer these research questions, we conducted a 2-fold, 3-round, 3-panel Delphi study with 16 experts, consisting of practitioners and researchers. The findings of this research show that there indeed exists researcher bias in identifying the drivers and barriers of AI adoption in workplaces. Further, it shows that the AI adoption factors and their priorities vary according to the respective business functions.

2 Background

2.1 Researcher bias

When a researcher influences the outcome of a study based on their expectations, either consciously or subconsciously, it results in a researcher bias (Romano et al., 2021). They are of two types, either stemming from a biased research design (Fagenson, 1990; McDonald, 2000) or by interaction with participants (Houston & Gremler, 1993; Kahn & Cannell, 1957). These biases could be the product of questionable research practices, or the researchers' expectation of a positive outcome to the concepts being studied, or the immaturity of the field under investigation (Romano et al., 2020). Further, simply the way a researcher interacts with a respondent can bias the answers of the respondent and potentially compromise the results (Miyazaki & Taylor, 2008). Yet, achieving complete control over researcher biases is considered infeasible (Miyazaki & Taylor, 2008). This underscores the need to examine disparities in perspectives between researchers and practitioners, in the context of AI adoption, because it could reveal potential areas of misalignment in theory.

Further, the lasting impact such researcher bias has on research discourse and its cascading implications on policy-related decisions is documented in many cases. For example, clinical intervention in empirical studies was affected by such a bias (Crossley et al., 2008), leading to findings that drove decisions favouring pro-industry outcomes (Berkman et al., 2014; Kunz et al., 2007). Researcher bias also leads to exaggerated effects, with around 80% of the effects reported in economics research being inflated (Ioannidis et al., 2017). Shepperd et al., (2014) used 600 empirical studies and established that researcher bias influences the outcome of the model being built. Similar critiques of research establishing the concept of biological determinism, which posits that human intelligence is dependent on race and economic status (Morton & Combe, 1839), show how empirical research by scientists exhibiting researcher bias could influence decades of public policy (Gould, 2003). One such example in the USA was the enacting of the Immigration Act of 1924 including the Asian Exclusion Act, that favoured immigrants from Northern and Western Europe while reducing the number of immigrants from other parts of the world, who were deemed to have lower intelligences based on these experiments that suffered from researcher bias (Gould, 2003).

Establishing such a bias, if it exists in IS research, will urge researchers to employ techniques to reduce it, thereby increasing the practical impact of research into the AI adoption process. This constitutes the first objective of this study.

2.2 Adoption factors hinging on business functions

Adoption factors of AI-based technology are usually studied for a business as a whole (Dasgupta & Wendler, 2019; Kar & Kushwaha, 2023; Kurup & Gupta, 2022; Solaimani et al., 2023). However, several sub categories of business functions like organisational management, innovation, and marketing, finance and HR possess unique operational contexts and objectives. In the context of organisational management, extant research shows that factors like effective implementation (Richards et al., 2019), technical compatibility, organisational readiness and users' expertise (Nguyen et al., 2022) enable successful adoption of AI tools. In the innovation context, other success factors play a role, such as availability of data (Liu et al., 2020; Mikalef & Gupta, 2021; Trocin et al., 2021), reduced cost (Liu et al., 2020) and organisational readiness (Mikalef & Gupta, 2021). The adoption of AI tools in the core business functions of marketing, finance and HR are yet again driven by other success factors like trust, usefulness, top management support (Pan et al., 2021; Wang et al., 2023), regulatory support, and financial readiness (Gupta et al., 2022). However, studies continue to build theories for AI as a whole. Establishing the unique factors and the priorities of each of them will benefit both researchers and practitioners (Radhakrishnan & Chattopadhyay, 2020). This is the second objective of this study.

In summary, the review of extant literature shows that the potential presence of a researcher bias is a challenge for theorising AI adoption factors. Moreover, domain-specific research on AI-adoption shows that adoption factors vary across business functions, which challenges the applicability of existing technology adoption models as theoretical lenses.

3 Methodology

This study adopted the Delphi method of inquiry, as prescribed by (Okoli & Pawlowski, 2004). It is a systematic and iterative approach, which elicits expert consensus on complex and uncertain topics (Okoli & Pawlowski, 2004). It is a suitable method to answer the outlined research questions, because it allows an investigation into the potential researcher bias affecting research on success and failure factors (pertaining to RQ1) and the differences in these factors between business functions and their prioritisation (pertaining to RQ2). The study was conducted over 10 months, spanning over 3 rounds of contemplation, in 3 different panels, with 2 types of experts and 16 participants.

3.1 Participants

16 experts participated in all of the rounds of the Delphi study, of which eight were practitioners and eight were researchers. As suggested by Okoli & Pawlowski, (2004), the first step in the study was to develop a Knowledge Resource Nomination Worksheet (KRNW). This list included 84 experts, of both researchers and practitioners. They were purposefully selected based on their expertise in organisational management, innovation, or core business operations like marketing, finance and HR. To participate, the researchers had to have published at least two papers in AI-based applications and the practitioners had to have at least two years of experience in working with AI-based tools. 58 of these experts were invited to participate in the study. We incentivised participation with gift vouchers equivalent to 80 Euros. 14 of the final participants accepted the gift voucher, two of them refused compensation. All the participants gave informed consent. Two participants withdrew from the study after round 1 resulting in 16 experts that finished round 3. In an effort to reduce socially desirable answers, in each of the 3 surveys the participants were reminded that their responses would remain anonymous, and they were not primed by quoting any success or failure factor beforehand (Joinson, 1999).

3.2 Procedure

The first round of the Delphi study commenced when the first Qualtrics questionnaire was sent to these experts. The objective of this stage of the study was to identify both success and failure factors of adoption of AI tools in workplaces, thus necessitating a two-fold study. All the experts were sent the same questionnaire that briefly explained the purpose of this research and asked them to list and explain factors that successfully and unsuccessfully influenced the adoption of AI tools at their workplaces (for the practitioners) and as dictated by their research (for the researchers). This resulted in 18 of the 58 experts returning the first round of the study. In total, the experts returned 278 responses, 107 for success factors and 171 for failure factors of adoption of AI. The responses were qualitatively analysed, using the template-based thematic coding technique (Cassell & Gillian, 2004). This method of analysis was found to be suitable because the responses identified themes of success and failure factors, and were viewed with a conventional positivistic position of quantitative social science. This method entailed reading each response and creating themes of factors discussed therein or adding them to existing themes and updating these for each of the consecutive responses. Finally, the language was unified, resulting in distilling these responses into a total of 22 success factors and 16 failure factors.

In the second and third rounds, the 18 participants were split into 3 panels, based on their expertise and research interests, as seen in Appendix A: the AI-driven organisational management panel (ORM), the AI-driven innovation panel (INN) and a panel of core business applications called the AI-driven marketing, finance and HR panel (MFHR), with 6 experts in each panel.

The objective of the second round was to solicit the priorities of each of the factors, as identified by the experts and their fellow panellists. For example, an expert in the INN panel was given one list of success factors and one of failure factors, that included their own responses from the first round and the ones from their fellow panellists, but not those of the ORM panel. The expert was asked to rank these factors by perceived priorities. In this round, all experts were informed of the panel they were added to, but during no part of the study were they informed about the names or any other identifiers of the other experts. This resulted in two lists (one each for success and failure factors) as ranked by each expert, exclusive to each panel.

The objective of the third round was to build a consensus of factors and their priorities among the panellists. The experts were now informed of the mean ranks of each of the factors (as calculated from the results of the previous round) and were given the opportunity to reconsider the ranks of each factor, based on the opinions of their fellow panellists. Each expert was a sent separate questionnaire (see appendix B) that included the list of factors, the mean panel ranks of each of the factors, a short explanation of the factor (as derived from all the responses of the panel) along with the rank they themselves had assigned to the factors in the previous round. The questionnaire mentioned that the experts could choose to retain the rank they had assigned to each factor or rerank the factors. This resulted in two lists of exhaustive factors that were first ranked and then reconsidered and reranked, thereby building a concordance of priorities of these drivers and barriers of AI adoption. The Delphi process employed in this study is visualised in Appendix C.

4 Results

The first objective of this study was to understand if there exists a potential researcher bias in the investigation of success and failure factors of AI adoption in the workplace (RQ1). The second was to investigate if and to what extent these factors differ between business functions (RQ2).

4.1 Researcher bias in AI adoption

We investigated a potential researcher bias by assessing the average ranks the researchers and practitioners assigned to the success and failure factors of AI adoption. A researcher bias is indicated if the average importance of factors differs drastically between researchers and practitioners. We assessed the Kendall's W factor as suggested by (Okoli & Pawlowski, 2004), which is a non-parametric measure of concordance, to elicit how much practitioners and researchers agree or disagree with each other. The factor ranges from 0 to 1; 0 indicating complete disagreement and 1 indicating absolute agreement. Tables 1 and 2 visualise the average ranks per factor for practitioners (P) and researchers (R) for each subpanel and for rounds 2 (before the consensus-making phase) and 3 (after the consensus-making phase). Kendall's W factors are indicated in the two bottom rows of Tables 1 and 2, to help interpret the consensus per group.

In the final round, the panellists of the ORM and INN panels had a substantial agreement (Schmidt, 1997) on the success and failure factors (with Kendall's W > 0.6). The panellists of MFHR had a fair agreement with Kendall's W of 0.346 and 0.386 for the success and failure factors, respectively. To assess the possibility of a researcher bias, each panel is broken down into subpanels of researchers and practitioners.

In support of a researcher bias, both the researchers and practitioners, among themselves, had a better agreement about the factors affecting adoption and their priorities. This agreement level drops when they are considered as a whole panel (i.e., combining researchers and practitioners). This is evidenced by 9 out of 12 (75%) of these subpanels having a higher agreement level, when compared to the whole panel, for the success factors and 11 out of 12 (92%) for the failure factors.

In the context of success factors, some of them like *availability of data* and *the fear of missing out* in ORM, *better forecasting* in INN and *ease of use* and *efficiency of the tool* in MFHR have perfect agreement among the subpanels. However, factors like *ease of implementation* in ORM and *ease of use* in INN have vastly different priorities. These differences drive the researcher bias, because practitioners and researchers do not consider the same factors to be as important.

Though the failure factors like *lack of trust* and *high implementation cost* in ORM, *algorithmic bias* in both INN and MFHR and *false outcomes* in MFHR show agreement, some others like *lack of user control* in ORM, *lack of trust* in both INN and MFHR and its *unnecessity* in MFHR show substantial divergence in prioritisation.

In summary, the agreement level within the subpanels (researchers and practitioners separately) is higher when compared to the panels. To assess the level of difference, the percentage change between the agreement levels of the subpanels to the panels were calculated for each round and each panel. This difference ranges from the lowest of 3.83% (the success factors as ranked by the researchers in the INN) to the highest change of 105.96% (the failure factors as ranked by the researchers in the MFHR panel). Hence, the data supports the existence of a researcher bias.

Table 1: The difference in success factor rankings among researchers and practitioners

Success factors	AI-driven organisational management (ORM)				AI-driven innovation (INN)				AI-driven marketing, finance and HR (MFHR)			
	Round 2 rank		Round 3 rank		Round 2 rank		Round 3 rank		Round 2 rank		Round 3 rank	
	P	R	P	R	P	R	P	R	P	R	P	R
Availability of data	4	3	1	1								
Better forecasting	6	2	11	11	10	12	12	12	6	5	5	6
Competitors usage	16	15	9	10	8	16	14	16				
Cost reduction	3	7	2	5	11	2	3	2				
Ease of implementation	10	6	12	15								
Ease of use	5	8	4	3	1	6	1	6	2	1	1	1
Easier task automation					7	8	9	8				
Easy implementation					16	9	16	9				
Efficiency of the tool	1	1	3	6	2	1	2	1	1	2	2	2
Fear of missing out	13	13	16	16	13	15	15	15				
Frequency of usage	9	10	8	4								
Human control	14	14	7	8								
Impact on deliverables					14	3	6	3	5	6	6	5
Knowledge of					15	4	13	4	3	4	4	4

Success factors	AI-driven organisational management (ORM)				AI-driven innovation (INN)				AI-driven marketing, finance and HR (MFHR)			
	Round 2 rank		Round 3 rank		Round 2 rank		Round 3 rank		Round 2 rank		Round 3 rank	
	P	**R**	**P**	**R**	**P**	**R**	**P**	**R**	**P**	**R**	**P**	**R**
the technology/ AI literacy												
Meticulous implementation	11	12	13	14								
Potential for innovation	7	9	10	9								
Quality of information					12	5	7	5				
Task automation	2	4	5	7								
Top management support/ Team support	8	5	6	2	9	14	11	14				
Trainability of the tool					3	13	8	13				
Transparency	15	11	14	13	6	11	10	11	4	3	3	3
Trust					4	7	4	7				
Kendall's W (for each subpanel)	0.442	0.647	0.919	0.816	1	0.389	1	0.786	0.327	0.365	0.250	0.629
Kendall's W (for each panel)	0.195		0.820		0.389		0.757		0.217		0.346	

Note: P = practitioners, R = researchers

Table 2: The difference in failure factor rankings among researchers and practitioners

Failure factors	AI-driven organisational management (ORM)				AI-driven innovation (INN)				AI-driven marketing, finance and HR (MFHR)			
	Round 2 rank		Round 3 rank		Round 2 rank		Round 3 rank		Round 2 rank		Round 3 rank	
	P	R	P	R	P	R	P	R	P	R	P	R
Algorithmic bias					9	12	12	12	10	6	9	9
Blackbox/ lack of transparency	5	11	7	10	10	10	10	9	6	8	6	7
Data privacy concerns/ regulations	1	2	1	2	1	3	1	2	5	7	7	3
False outcomes	10	6	6	9					4	5	5	5
Fear of missing out	13	13	13	12								
High implementation cost	4	8	5	5	5	4	4	1	1	1	1	2
Implementation time constraints					2	2	2	3				
Incompatibility with existing IT infrastructure					3	1	3	5				
Inefficient tool	8	5	9	7	8	7	7	6	2	3	2	4
Lack of clean data	6	3	2	3	12	11	11	8	8	11	11	8
Lack of data	3	1	3	1					7	10	10	6

Failure factors	AI-driven organisational management (ORM)				AI-driven innovation (INN)				AI-driven marketing, finance and HR (MFHR)			
	Round 2 rank		Round 3 rank		Round 2 rank		Round 3 rank		Round 2 rank		Round 3 rank	
	P	R	P	R	P	R	P	R	P	R	P	R
Lack of expertise	2	9	4	4								
Lack of trust	7	7	8	8	4	9	8	11	9	2	8	10
Lack of user control	11	4	10	6	6	5	5	4				
Not necessary	9	12	12	13					11	9	4	11
Operational challenges	12	10	11	11	7	6	6	7				
Kendall's W (for each subpanel)	0.438	0.395	0.553	0.748	1	0.382	1	0.630	0.168	0.335	0.481	0.795
Kendall's W (for each panel)	0.249		0.603		0.259		0.608		0.074		0.386	

Note: P = practitioners, R = researchers

4.2 AI adoption in different business functions

To answer RQ2, from the second round onwards, we broke up the experts into 3 panels. The success and failure factors of adoption exhibited notable discrepancies across the three panels, in both their identification and prioritisation. This supports RQ2, by highlighting the inherent differences in AI adoption across different business functions. The specific factors are visualised in Figure 1 and are discussed next.

The five success factors common among all panels are *better forecasting*, *ease of use*, *efficiency of the tool*, *transparency of the tool* and the *AI literacy* of the users. The MFHR panel has no unique driver or barrier of AI adoption, suggesting that the operationalisation of AI tools in such work functions highly overlap with other AI systems, like the ones used to drive innovation or organisational management. Further, the INN and ORM panels have the highest level of bi-panel overlap of five factors (*competitors' usage, cost reduction, fear of missing out, human control and top management or team support*). This indicates that the drivers of business functions that require efficiency and scalability (for organisational management) and creativity and generative models (for innovation) share operational commonalities. In support of RQ2, 50% of success factors were unique and panel-specific, while only 23% of them were common across all the panels.

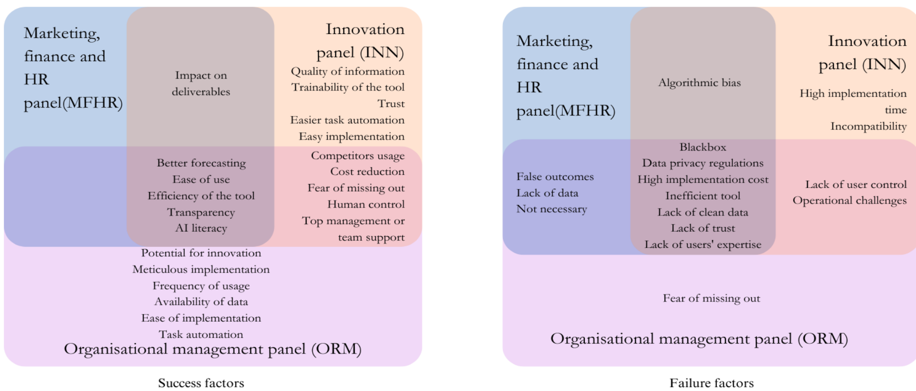

Figure 1: Success and failure factors of AI adoption identified by the 3 panels
Source: Own

The seven failure factors common to all three subpanels were: *AI being a black box, data privacy regulations, high implementation costs, inefficient tools, lack of clean data, lack of trust* and *lack of user expertise*. The ORM and MFHR panels share three common failure factors, including AI tools providing *false outcomes, lack of data* and it *not being necessary*. In summary, 43% of the failure factors were common among all the panels and 19% were unique panel-specific factors. This indicates that in contrast to success factors, most failure factors are applicable across business functions.

We complemented this descriptive analysis with a correlation analysis on the normalised ranks of the 5 success and 7 failure factors common between the 3 panels. This revealed a high correlation ($r = 0.879$) between the priorities of the common success factors as determined by the ORM and INN panels. The same was high between the INN and MFHR panels (r = 0.859) and the ORM and MFHR panels (r = 0.844). Hence, this indicates that experts prioritised success factors which are common across all application domains similarly important.

The agreement on the priority levels of the 7 common failure factors is more contrastive. The correlation of the ranks between the panels was significantly lesser, with r = 0.307 between the ORM and INN panels, r = 0.365 between the INN and MFHR panels and r = 0.002 between the ORM and MFHR panels. This suggests that experts ranked the importance of the common failure factors dissimilarly. The contrast in these agreement levels across panels underscores the diverse nature of AI's application in different business contexts and highlights the need for tailored evaluation frameworks within distinct application areas.

In summary, providing further support to RQ2, the analysis shows that the unsuccessful adoption of AI tools is influenced by domain-specific objectives and priorities, and the success factors seem to stem from systemic issues that cut across business functions.

5 Discussion

This study identified a potential researcher bias in the examination of the adoption factors of AI tools in workplaces. Beginning with the success factors, several disparities were identified, first on the matter of implementation of AI tools, where a researcher (RE026) who ranked it high, claimed, "...should be an incremental process ensuring inclusion", while a practitioner (PE011) who ranked it low wrote, "Integrating into existing software…as for any software." Similarly, a researcher (RE021) discussing the ease of use ranked it low, and wrote, "Usability… as for any software", while a practitioner (PE010) who ranked it high wrote, "...a key, especially for a non-technical person." Further, a similar trend of disagreement was seen in the discussion of failure factors like lack of user control, when a practitioner (PE040) who ranked it high claimed, "...some functions should be overridable by human intelligence", but a researcher (RE010) who ranked it low opined, "lack of control in the decision-making process…is hard to analyse why a particular output is given." Trust in the AI tool was another contentious factor, with a practitioner (PE040) claiming, "...trust is a huge factor in research but not in industry…". This claim seems to be true as a researcher (RE022) wrote, "I thought this (trust) would be top

1…". The other disputed failure factor was the unnecessity of AI tools. A practitioner (PE010) who ranked it high claimed, "...would not want to switch…if necessity is not seen.", however a researcher (RE018) who ranked it low, wrote, to justify the low rank, "AI adoption comes from a strategic level", insinuating that the actual users may not make decisions about its necessity.

Given these inconsistencies in the identification of adoption factors between researchers and practitioners, and the fact that researchers' opinions could shape the outcome of a study (Romano et al., 2021), it is beneficial to reconsider the research direction in order to ensure that future research on the matter sufficiently represents the reality it examines.

Secondly, this study also shows that success and failure factors are unique to different business functions and that they are varied in their prioritisation. The reason for the differences in AI adoption could be explained by the unique capabilities that AI offers for different contexts of usage. For example, in organisational management it is used to streamline processes and enhance employee efficiency, but in the innovation domain, it is used to foster creativity and research, but in core business domains of marketing, finance, and HR, it is used majorly as predictive analytics for advertising strategies and talent acquisition through natural language processing algorithms.

To further this point, current research in organisational management focuses on effective implementation (Richards et al., 2019), technical compatibility, organisational readiness and users' expertise (Nguyen et al., 2022). But in the same context, this research brings to light other success factors like the AI tool having a potential to drive innovation and its frequency of usage. Similar observations can be made for failure factors and the 2 other business functions being studied here, but are not elucidated due to space constraints. These findings underscore the need for future research to explore these newfound factors in specific contexts of usage, to build theory that more closely reflects reality.

6 Contribution

6.1 Theoretical contributions

Our findings uncovered the presence of a potential researcher bias in studies of AI adoption factors in the workplace. The ramifications of such a researcher bias could range from potential distortion of research findings (Miyazaki & Taylor, 2008), to wrongly impacting policy creation, to perpetuating certain perspectives that may not reflect the reality they represent (Chenail, 2016). This study serves as a stepping stone to acknowledging this bias so that researchers can employ methods to counteract this bias, as suggested in (Chenail, 2016; Romano et al., 2020).

Our findings also show that AI adoption factors differ across business functions and are assigned different priorities. Most success factors are not common across business functions and mostly have dissimilar priorities. In contrast, different business functions often share the same failure factors but are assigned different priorities. With this, we enrich the current discourse on AI adoption in the literature, which study AI adoption for business as a whole (Bérubé et al., 2021; Dasgupta & Wendler, 2019; Kar & Kushwaha, 2023; Kurup & Gupta, 2022; Solaimani et al., 2023), because existing cross-domain adoption theories can only cover a part of the bigger picture. However, this study encourages researchers to step away from examining the drivers and barriers of AI adoption in workplaces holistically, and take into consideration the unique operational contexts and objectives. This implies that domain-specific theories may be needed to best explain and predict AI adoption.

6.2 Practical contribution

For practitioners, this research offers curated lists of success and failure factors that can serve as a navigational framework for AI adoption initiatives. For example, if a customer segmentation tool is slated to be adopted for marketing purposes in an organisation, they can prioritise the ease of use and the efficiency of the tool (ranked 1 and 2 respectively, by the MFHR panel), as opposed to a supervised learning model being used to track employee performance in an organisation, where the availability of data should be taken into consideration first (ranked 1 by the ORM panel). This extends to the factors that hinder the adoption of AI tools as well. This study is rich with ranked lists in 3 different business functions, discussed over 3 rounds, providing valuable insights to all stakeholders involved to foster the adoption of such tools in the workplace.

6.3 Methodological contribution

Finally, in a contribution to research methodology, to the best of the knowledge of the authors, this is the first paper to employ a dual-fold Delphi study. Delphi studies are usually conducted over one phenomenon and build consensus on the matter at hand. In this study, two distinct but related themes of the success and failure factors of AI adoption were discussed and a consensus was drawn. As shown in the results, the factors that foster better adoption do not necessarily hinder the adoption in their absence, in the same level of priority. For example, the efficiency of the tool was discussed to have the highest priority as a success factor by the INN panel, however, inefficiency of the tool was not the highest ranked failure factor, but was ranked as the 6th most important failure factor by the same panel. Expanding the Delphi study to encompass a dual focus (both success and failure factors), researchers can uncover nuanced insights of the matter, by unearthing asymmetric causal relationships (Wagemann et al., 2016).

7 Limitations and future research

This study suffers from a few limitations. 16 experts were involved in all three rounds. Even though this is a fairly adequate sample size of experts in a Delphi study (Okoli & Pawlowski, 2004), we would have liked a larger sample to better represent the underlying populations. For example, the practitioners in the INN panel were all involved in software development, which could explain why their assessment of AI-literacy was rather low. Adding practitioners with a business background could overcome this limitation. To add to the robustness of the findings, future research could verify the findings through a survey of practitioners.

Another limitation of this study is that we could not definitively assess researcher bias for the MFHR subpanels due to the limited number of factors generated and that concordance levels within subpanels were generally low. One of the reasons could be that business disciplines such as marketing, HR and finance may involve more diverse interpretations and understanding of the AI technology and could result in lower concordance levels due to the inherent complexities and variations in assessing performance or impact. Thus, we recommend splitting marketing, finance and HR into separate panels.

Future researchers can extend the expert pool to include decision makers in organisations. This will produce a more rounded understanding of the third stakeholder involved, the decision-makers in institutions, as opposed to the 2 primary stakeholders in the research of AI adoption factors, the practitioners and the researchers.

8 Conclusion

This paper employs the Delphi method to demonstrate the researcher bias present in studies that examine the adoption of AI tools in the workplace. Further, the findings show that diverse business functions of organisational management, innovation, and marketing, finance and HR possess both similar and dissimilar drivers and barriers to adoption of AI tools, and that these vary in their priorities across the panels. Further, through a two-fold study, this paper elucidates that a factor which could drive the adoption of an AI tool, need not necessarily hinder the adoption in its absence, in the same level of priority. Finally, this paper provides lists of drivers and barriers of AI adoption and their priorities, as decided by both researchers and practitioners, for 3 distinct business functions, which could help practitioners and policy makers foster better adoption practices at their workplaces.

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Appendix A

Table A: The expertise of each of the panellists

<table>
<tr><th colspan="3">Researcher</th><th rowspan="2">Panel assigned</th><th colspan="3">Practitioner</th></tr>
<tr><th>Research area</th><th>Job title</th><th>Gender</th><th>Field of work</th><th>Job title</th><th>Gender</th></tr>
<tr><td>AI in data driven decision support, auditing AI and data-driven business models</td><td>Professor</td><td>Male</td><td rowspan="3">AI-driven organisational management (ORM)</td><td>Project management</td><td>Project manager</td><td>Male</td></tr>
<tr><td>AI in organisations/ management</td><td>Senior researcher</td><td>Male</td><td>IT Department</td><td>Chief Information Officer</td><td>Male</td></tr>
<tr><td>AI in organisations</td><td>Associate professor</td><td>Male</td><td>Project management</td><td>Product director</td><td>Female</td></tr>
<tr><td>AI in policy</td><td>Researcher in interactive intelligence</td><td>Male</td><td rowspan="3">AI-driven innovation (INN)</td><td>Software development</td><td>Principal architect</td><td>Male</td></tr>
<tr><td>AI in innovation, product design</td><td>Research associate</td><td>Female</td><td>Software development</td><td>Senior software engineer</td><td>Male</td></tr>
<tr><td>AI in software development</td><td>Assistant professor</td><td>Male</td><td>Software development</td><td>Director of delivery</td><td>Male</td></tr>
<tr><td rowspan="2">AI in finance and risk management</td><td rowspan="2">Professor</td><td rowspan="2">Male</td><td rowspan="4">AI-driven marketing, finance and human resources (MFHR)</td><td>Finance/ risk management</td><td>Financial consultant</td><td>Female</td></tr>
<tr><td>Marketing and sales</td><td>Sales engineer</td><td>Male</td></tr>
<tr><td rowspan="2">AI in marketing and sales</td><td rowspan="2">Assistant professor</td><td rowspan="2">Female</td><td>Human Resources</td><td>Human resources analyst</td><td>Male</td></tr>
<tr><td>Data usage in SME market</td><td>Data project lead</td><td>Female</td></tr>
</table>

Appendix B

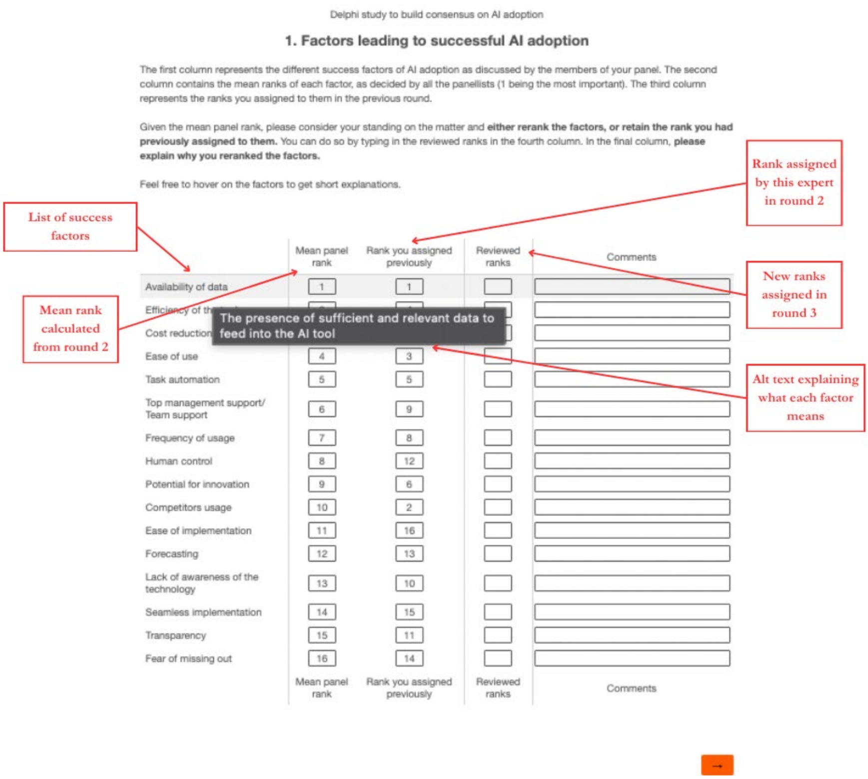

Figure B: One of the unique questionnaires sent to an expert in the ORM panel, for the third round of the Delphi study

Source: Own

Appendix C

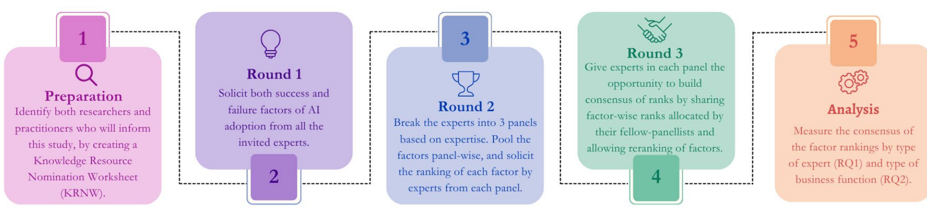

Figure C: Visualisation of the Delphi process of this study

Source: Own