Organizational Challenges in Adoption and Implementation of Artificial Intelligence

Marigo Raftopoulos
Tampere University
marigo.raftopoulos@tuni.fi

Abstract

Our investigation into the organisational challenges in the adoption and implementation of artificial intelligence reveals complex dynamics in the interplay between strategic decision-making, implementation, enablement and performance outcomes. We undertook a study of the views of international industry experts on the enablers and barriers of adopting and implementing AI and found five thematic clusters of issues affecting project success and value creation. We contribute to theory development and a conceptual model on navigating organisational adoption and implementation of AI technology.

Keywords: Artificial intelligence, strategic decision-making, digital transformation, AI enablement.

1. Introduction

We have limited knowledge about the necessary and unique attributes a successful organisational implementation of artificial intelligence (AI) in business applications (Pumplin et al., 2019). Recent studies suggest that many organisations are falling short in creating tangible business value through AI (Shollo et al., 2022) and that returns on AI investment are below expectations (Mikalef & Gupta, 2021). The failure to realize the potential of AI-enabled technologies is largely attributable to the oversimplified, yet pervasive ways that society and organisations treat the relationship between AI and humans in the value creation process (Metcalf et al., 2019). Furthermore, the advancement of AI us evolving well beyond being treated as mere technological tools for human use and are instead becoming capable of operating as interdependent agents (Fügener et al., 2021; Seeber et al., 2020). This is creating the unprecedented challenges to current models of strategic decision making, technology investment, human-machine collaboration, and business and organisational transformation (Berente et al., 2021; Collins et al., 2021). Uncertainty and instability created by the speed of AI technology advancement, changes in the regulatory environment with regards to the development and scaling of AI technologies, and uncertainty in current economic conditions have created a challenging environment that organisations need to navigate to achieve sustainable AI-led digital transformation (Dwivedi et al., 2021). Given this context, we undertook a study of the views of ten international industry experts on the enablers and barriers of adopting and implementing AI. We draw on the behavioral theory of the firm (BTF) to understand the complex dynamics surrounding AI adoption and implementation. BTF is influential in the fields of strategic management and organization theory (Gavetti et al., 2012; Cyert & March, 1963) and provides a useful framework that complements information systems research. The key tenets of BTF seek to explain how organisations engage in decision-making for investing in innovative technologies (Cyert & March, 1963; Lewellyn & Bao, 2015) and thereby provide insight for current global challenges in AI adoption. As such, we designed our research based on our research question: What are the current challenges with business adoption and implementation of AI?

We sought perspectives from ten AI solution providers, strategic advisors and consultants that work directly with organisations in investing and implementing AI technologies predominantly in the USA and Europe. Our findings show that there is a complex heterogeneity of issues surrounding AI adoption, implementation and subsequent value-creation. These issues are clustered in five groups of macro-environmental factors, technology maturity issues, strategy and leadership, systems enablement, and the shifting nature of work. We conclude our paper with a contribution to theory development and a conceptual model on the factors affecting organisational adoption and implementation of AI technology.
2. Theoretical foundation

The BTF is considered a landmark behavioral theory of the firm developed by Cyert & March (1963) concerned with the way organisations make economic decisions to create business value. Related works using BTF include the implications for innovation management of AI technologies and machine learning-based AI systems (Haefner et al., 2021), the bounded rational process of managerial decision making for technology investment (Dong et al., 2013), and firm international investment decision-making (Surdu et al., 2021). BTF posits the importance of the role of managers’ heuristics and cognitive biases in explaining variation in strategic decisions (Argote & Greve, 2007; Lewellyn & Bao, 2015). This provides insight into situations where organisational behavior is complex, dynamic and heterogeneous as is evidenced in the literature and in our research into AI adoption.

One of the key tenets of BTF relevant to our study is that firms comprise of multiple stakeholders and goals. Organisations are often described as a coalition of different stakeholders such as shareholders, managers, and employees, and each have their own business goals and expectations. Furthermore, there is not a simple relationship between these different and often competing goals and subsequent decision-making (Cyert & March, 1963) and organisations are in a perpetual state of quasi-resolution of conflict and seek to negotiate a more predictable operating environment. Another insightful tenet is that explains behavior in complex contexts is that firms do not optimize, they suffice. In environments with information asymmetries, management decision-making is problem directed by engaging in problemistic search prompted by finding a sufficient solution to a specific problem which may not necessarily an optimal one (Surdu et al., 2020; Mahoney, 2004). Decisions to suffice are not always rational as they are influenced by emotion and bias. Closely tied to sufficing is uncertainty avoidance, where organisations avoid the requirement to correctly anticipate future events and trends by using decision rules that emphasize short-run reactions to short-run feedback. This behavior tends to focus on maintaining the status quo over proactive transformation (Surdu et al., 2020). The final tenet is continuous organisational learning and adaptation. Managerial decision-making is an adaptive process of organizational learning from performance feedback. However, they often repeat strategies that have worked in the past and show a bias in favor of solutions that they are familiar with (Mahoney, 2004).

As intelligent technologies proliferate throughout organizations the process of making strategic decisions is becoming more complex and uncertain (Faraj & Leonard, 2022). Furthermore, the blurred boundaries between AI technology development and use makes it necessary to theorize beyond narrow approaches for a more accurate approximation of current and future challenges (Waardenburg & Huysman, 2022; Wagner, 2020). This becomes a pressing issue given the lack of consensus on the mechanisms that can generate business value from AI (Mikalef & Gupta, 2021).

3. Methodology

Prior to this research we had conducted an extensive systematic literature review to scope the extant literature on enablers and barriers to organization adoption of AI (Rafitopoulos & Hamari, 2023). The key themes that were identified in the literature formed four clusters of implementation challenges: human, organization, strategic and technology factors. While the literature review provided important insight on the enablers and barriers of AI adoption, there remained a gap in understanding the strategic decision-making and behavior of organisations investing and implementing AI. Therefore, we designed a study using expert interviews to investigate this specific gap. Our key objective was to ground-truth the findings of our literature review and seek a deeper understanding of the issues affecting organizational experiences with AI implementations. We identified that this is an effective method to complement and contextualize findings of a literature review (Lutz et al., 2019).

We adopted the definition of an expert to be an individual with advanced knowledge in the investigated field of research (Meuser & Nagel, 2009). Our focus was on the identification and selection of industry experts who had specialized experience in the procurement, development, or implementation of AI technologies in organisations. We identified a range of industry experts through a scanning of social media activity on LinkedIn and Twitter, which included a scan of our own professional social media networks. For example, we curated a Twitter list of 380 accounts that we verified as credible, active and influential industry and academic experts in AI. We decided to focus our selection of experts operating as consultants, advisors and AI technology solution providers to organisations. The experts we selected had extensive experience across multiple AI projects, technologies, use cases and organisations, and had a comprehensive overview of issues and patterns of organisational decision-making on AI adoption and implementation. This formed our search criteria on their LinkedIn and Twitter accounts, and we verified with the expert when
we first contacted them. A key advantage of this expert group is that they also have intimate technical knowledge of AI technology development. In terms of sample size, we followed the recommendations of Creswell and Creswell (2018) who suggest using between three and ten experts. A total of 15 experts were initially contacted via email or direct messaging on social media channels, five had declined or not responded before we reached our target. We found that ten experts represented a good sample as we quickly reached a conceptual saturation point after eight interviews. In Table 1 we provide a profile of the ten experts that included four senior C-suite level executives at global technology companies; three global consultants and former technology executives who provide advisory services to industry and policy makers focusing on AI; two technology executives at AI innovation hubs servicing organisations looking to invest and experiment with AI technologies; and a machine learning specialist at a global technology consultancy. For the gender breakdown, two identified as female (F) and eight as male (M).

### Table 1. Profile of experts

<table>
<thead>
<tr>
<th>Expert, position &amp; base geographic location</th>
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<tbody>
<tr>
<td>1 Machine Learning Specialist (F), Global Technology Consultancy, Asia-Pacific</td>
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<tr>
<td>2 Global Technology Consultant (M), Technology Executive Advisor, EU &amp; USA</td>
<td></td>
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<tr>
<td>3 Technology Executive &amp; Consultant (M), EU Policy Advisor on AI, EU and USA</td>
<td></td>
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<tr>
<td>4 Technology Entrepreneur (M), Company Executive &amp; Consultant, EU, Nordics &amp; India</td>
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<tr>
<td>5 Customer Success Executive, (M), Global AI-ML Technology Company, USA</td>
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<tr>
<td>6 Technology consultant (F), AI Technology Incubator, Finland</td>
<td></td>
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<tr>
<td>7 CEO, (M) Global AI-ML Technology Company, USA</td>
<td></td>
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<tr>
<td>8 Technology consultant (M), AI Technology Incubator &amp; Innovation Lab, USA</td>
<td></td>
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<tr>
<td>9 CEO, (M) Global AI-ML Technology Company, USA/GLOBAL</td>
<td></td>
</tr>
<tr>
<td>10 CTO, (M), Global Technology Consultancy Company, USA</td>
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Examples of expert experiences with a range of AI implementations included medical imaging, customer profiling, supply chain optimization, automated detection models, big data analytics, image to text recognition systems, and risk management and statistical process models.

We conducted semi-structured interviews consisting of four core questions designed to address our research question: (1) What is the current state of business interest and investment in AI technologies? (2) What challenges are you seeing with business adoption and implementation of AI technologies? (3) What would you describe as the key barriers and enablers of AI adoption and its overall performance once implemented? (4) What are the key opportunities for improvement from your experience?

Interviews were conducted between April-June 2023 and held online through Zoom. Interviews were audio recorded in Zoom then immediately transcribed with specialist software, Otter.ai. The transcriptions were then downloaded from Otter.ai into MS Word, were anonymized, cleaned, and corrected errors in the transcriptions. An example of a transcription error is when the transcript read “hard” rather than “large” (language models). The duration of each interview averaged around 45 to 75 minutes and were held by the first author. The clean transcriptions were then uploaded into specialized qualitative software Atlas.ti and were coded in detail using a codebook we developed for the study.

The first round of open coding was informed by the methods of Williams and Moser (2019) and utilized the Atlas.ti software. We identified and organized the data into 161 initial codes and collected unique quotes from the experts for each code to capture nuance and meaning. Axial coding was applied in the second level of coding to further refine, align, and categorize the themes identified in the first round of open coding. Keeping in mind that the purpose of this phase is to create distinct thematic categories (Williams & Moser, 2019) we conducted several iterations of continuous clustering and distillation using thematic analysis and grounded theory methods to establish relationships between the themes in the data (Strauss, 1998). After several iterations we settled at 19 key code groups derived from the 161 codes that represented the range and depth of the views of the ten experts. Using selective coding in the final step of our data analysis (Strauss, 1998) our aim was to integrate and refine the code groups into key categories to form a larger theoretical scheme. After several iterations we settled on five distinct cluster groups of macro-external environment factors, technology factors, strategy and leadership issues, enablement of AI implementations, and the nature of work. A summary is provided in Table 2.

We found challenges in initially conducting the thematic analysis due to an unexpected high concentration of themes under the two clusters of macro-external and enablement. By comparison, the themes under the other three clusters were familiar to us from our prior research as they presented as commonly occurring themes in extant literature.
4. Key findings

We found a complex array of inter-related issues affecting the strategic decision making and behavior of organisations in relation to AI adoption and implementation. A presentation of our key findings is detailed below by the five key categories.

4.1. Macro External Factors

The macro cluster featured external influences in shaping organisational concerns and decision-making on AI adoption and implementation. **Economics issues** such as securing comparative advantage through improved scale and efficiency is front of mind for organisations adopting AI. Expert opinion however was divided on the type of impact AI will have on organisations and the global economy. Several noted that it will be a significant disruption with consequences greater than the last industrial revolution. Economic factors were also heavily influenced by the unknown directions of the **regulatory and policy environment**, particularly in the EU and USA where deliberations were taking place at the time of the interviews. There is widespread consensus that some regulation is needed to provide guardrails against unethical practices, immature technologies, and malicious actors. However, the majority of experts expressed concerns in four key areas, (1) that too much regulation would stifle innovation, (2) will negatively impact or slow down industry adoption of AI technologies, (3) play into the hands of the largest 3-4 technology companies seeking economic rent by raising barriers to entry for the next tier of technology developers and startups, and (4) AI adoption would be concentrated in larger corporations who would be able to resource the new AI compliance requirements relative to smaller businesses. **Democratization and activism** featured highly with experts who operated in multiple geographies and were conscious of the unequal distribution of access to AI technologies and their benefits. A key element in these discussions focused on the need to maintain cultural, linguistic and intellectual diversity which are potentially threatened by generative AI trained largely on content derived from the English-speaking internet. Several experts mentioned the need for technical sovereignty in their particular regions i.e., the Nordics and India were mentioned here. The ownership and control of key AI technologies were thought to be an area of concern.

**Factors in relation to Futurism** or anticipation of future trends, ranged from a broad range of perspectives: (a) an overestimation of current and future AI capability unduly influenced by business hype and science fiction, (b) the invisibility of future trends which is creating uncertainty or lags in AI investment decision-making, and (c) concerns about the uneven flow of costs and benefits across society, and that this signals a need systemic change and adaptation, but across unknow timelines. The following quotes from the interviews highlight the key

### Table 2. Summary of categories and codes

<table>
<thead>
<tr>
<th>Categories and Codes</th>
<th>Subcodes</th>
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<tbody>
<tr>
<td>Macro: Democratization &amp; Activism</td>
<td>11</td>
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<tr>
<td>Macro: Economics</td>
<td>10</td>
</tr>
<tr>
<td>Macro: Futurism &amp; Trends</td>
<td>13</td>
</tr>
<tr>
<td>Macro: Policy and Regulation</td>
<td>9</td>
</tr>
<tr>
<td>Technology: Technical Sovereignty</td>
<td>5</td>
</tr>
<tr>
<td>Technology: Technology Maturity</td>
<td>19</td>
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<tr>
<td>Technology: Value Destruction</td>
<td>10</td>
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<tr>
<td>Strategy &amp; Leadership: The Unknown</td>
<td>8</td>
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<tr>
<td>Strategy &amp; Leadership: Early Stages</td>
<td>4</td>
</tr>
<tr>
<td>Strategy &amp; Leadership: Holistic</td>
<td>5</td>
</tr>
<tr>
<td>Strategy &amp; Leadership: Investment</td>
<td>2</td>
</tr>
<tr>
<td>Enablement: Systems Integration</td>
<td>10</td>
</tr>
<tr>
<td>Enablement: Human Integration</td>
<td>5</td>
</tr>
<tr>
<td>Enablement: Literacy &amp; Education</td>
<td>7</td>
</tr>
<tr>
<td>Enablement: Proof of Concept</td>
<td>9</td>
</tr>
<tr>
<td>Enablement: AI Acceptance</td>
<td>9</td>
</tr>
<tr>
<td>Nature of Work: Devaluation</td>
<td>7</td>
</tr>
<tr>
<td>Nature of Work: Human Capability</td>
<td>8</td>
</tr>
<tr>
<td>Nature of Work: H-M Teamwork</td>
<td>10</td>
</tr>
<tr>
<td>5 Categories; 19 key code groups</td>
<td>161</td>
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The conceptualization stage in our thematic analysis, where Meuser and Nagel (2009) suggest to look at specific characteristics of the commonly shared knowledge of the experts to condense and formulate categories, was instrumental in finalizing our results. It was clear that the ‘commonly shared knowledge’ of our experts as vendors of AI technology solutions, was their detailed knowledge of the enablement of their technologies, and an awareness of the macro external factors that have an impact on their sales cycles. This had enabled us to condense our initial analysis of subcodes, code groups and categories while still maintaining the integrity of the story that was unique in this data set. Our final stage was theoretical generalization (Meuser and Nagel 2009) where we represent the research results as empirically generalized findings. This was done by referencing our findings to the theoretical foundation of BTF and developed a conceptual framework to guide industry practice and contribution to theory.
There are several well-organised ecosystems. Once again, they viewed human technology needs to become an afterthought in designing for only one part of a complex organization, thereby becoming standalone. Several experts noted it as a natural outcome of the evolution and maturity cycle in the organization. The following quotes illustrate a few of the key technology factors raised by the experts:

“One of the major prohibiting factors is the actual access to good data. Companies have all these convoluted schemas and terminologies, but the data going in there is still exceptionally difficult to understand.” (E9)

“When dealing with neural networks and deep learning, there’s an innate randomness to it. So, you always need to be careful with its accuracy and insight. It’s not as straightforward as automation.” (E1)

4.2. Technology Factors

Technology factors affecting AI adoption covered three key areas of technology maturity, technical sovereignty and value destruction. Technology maturity was the largest category and contained the well-known issues affecting AI efficacy and adoption such as accuracy, transparency and trustworthiness, limitations in algorithms for complex, high cognitive tasks, and the limited fine motor skills in robotics. At the root of many of these immaturities are an outcome of limitations in the availability and appropriateness of data for machine learning and the machine learning models. Experts maintained that the challenges in relation to data are significant and stem from access to good comprehensive data which is hampered by difficult data structures and strategy. There was consistent agreement amongst all the experts that issues and concerns in relation to technology maturity were legitimate, however it was explained that it was a natural outcome of the evolution and maturity cycle of these emergent technologies that will be improved over time. Experts agreed that industry needs to understand these limitations and be a proactive part of the development of solutions.

Limitations in technology design was mentioned as key issues that affects in-human-machine augmentation and subsequent value creation. Experts noted that narrow AI systems are often designed standalone and were conscious of the limitations of designing for only one part of a complex organization system, particularly when human-centered design becomes an afterthought. Experts agreed that technology needs to be better designed to complement human capability and fit within the wider organisational ecosystem. Once again, they viewed these limitations as an outcome of the early stages of development. AI design-related issues became a recurring theme in the interviews.

While AI’s known value creation potential are well documented and accepted, experts maintain that there are several potential value destruction factors affecting AI adoption. Issues that were mentioned include misinformation and disinformation through the action of bad actors, AI efficacy does not live up the promise experienced in controlled pilots, through to deliberate misuse of AI systems were users seek to ‘beat the AI’, make the system fail, or where they seek to jump the guardrails. A final factor mentioned by experts was the perceived need for organisations to maintain their technical sovereignty to manage technological risk such as cybersecurity, data security and leaks. The following quotes illustrate a few of the key technology factors raised by the experts:

“One of the major prohibiting factors is the actual access to good data. Companies have all these convoluted schemas and terminologies, but the data going in there is still exceptionally difficult to understand.” (E9)

“When dealing with neural networks and deep learning, there’s an innate randomness to it. So, you always need to be careful with its accuracy and insight. It’s not as straightforward as automation.” (E1)

4.3. Strategy and Leadership

The strategy and leadership cluster focused on three key areas: leading through complexity, needing a holistic approach towards AI adoption, and the need for a long-term investment strategy. In leading through complexity, experts maintain that very often organisational leaders did not know where to start and underestimate how much commitment would be required. Overall, organisational strategic direction on AI tends to be unclear. The reasons were diverse and ranged from (a) divided attention with climate issues, which often take precedence in the minds of leaders, (b) a lack of foresight and forward planning, (c) tend to have a skeptical mindset towards AI but are investigating to not be left behind, (d) lack of strategic objectives as they’re not sure what business problem they’re looking to solve. General consensus among the experts is that the advancement of AI technology is proliferating and unpredictable directions which is placing pressure on business leaders. Several experts maintain that most businesses are currently in the early investigation stages and still believe adoption of larger-scale AI is too risky given the large startup costs. However, experts believe that these positions are uninformed and the best option for organisations is to form meaningful strategic partnerships to mentor them through these early stages. In terms of holding a long-term investment strategy several experts maintain that organisations operate on inappropriate metrics and time horizons to assess AI performance. There was a unanimous position that popular construct of ‘return on investment’ is inappropriate and sets up
the AI investment for failure. The biggest pain point for AI adoption is the investment that starts from an initial startup cost for a pilot which then progresses to an unknown funding horizon depending on strategic direction, the complexity of the integration, and the required development costs. Experts emphasized that deployment is a one-off cost, but maintenance costs, such as ongoing machine learning, can be significant and must be planned for.

Very often, a parallel transformation in other parts of their organization to adequately integrate the AI technology. Many businesses won’t continue beyond the experiment or proof of concept due to the magnitude of change that it will require. In terms of a holistic approach towards AI adoption, several experts noted that organisations often made the following mistakes: (a) overfocus on the technical and financial side of AI and less so on the human and systems enablement, (b) little internal organisational dialogue or consultation about an AI strategy, (c) adopting a ‘set and forget’ strategy where businesses adopt AI in one area of the business but do not nurture its growth and ongoing development, or instigate the necessary structural changes in the organization to support it. The following interview quotes illustrate the concerns in relation to strategy and leadership:

“COVID showed many companies that they did not have a plan. They now realize that if they don’t have AI related technological intervention plan, it may leave their businesses very exposed.” (E2)

“There seems to be two types of companies, those who are very interested in their human employees’ well-being and their acceptance of the technology. The other type is purely interested in cost and productivity numbers, and that’s around 70% of our clients.” (E8)

4.4. Enablement of AI Implementations

Enablement of AI implementation was the largest cluster and comprise of five key categories: challenges with technology acceptance, systems integration, human integration, the importance of AI literacy and education, and the development of effective proof of concepts (PoC). In terms of AI technology acceptance, the majority of the challenges raised focused on the fear and identity loss arising from jobs being altered, devalued or lost. The second component of AI acceptance was the need for an understanding of how the technology works and this had aligned with classic technology acceptance models. Several experts noted that technology acceptance has significantly improved since the recent introduction of popular consumer-facing generative AI applications such as ChatGPT, MidJourney, and DALL*E which showed the general public that AI can enable humans to attain highly creative and productive endeavors. The key learnings of this phenomenon emphasized by the experts are (a) showing evidence to the public of how it enables humans, and not just simply telling them so, and (b) it empowered the individual as opposed to an employer or business.

In terms of systems integration four recurring themes were identified: the challenges of integration with existing legacy systems, the importance of forming strategic partnerships with external AI specialists, the need for systemic change to the organization to accommodate and AI-first operating model and renewing and upgrading the organization’s data strategy. In terms of human integration experts emphasized the importance of building and integrating advanced technology systems, particularly in areas that require high cognitive function, need to be designed with the human in the lead with the final analysis or decision making. The range of terms that were used by the experts include human oracles, human judge and humans-in-the-loop. Experts emphasized the need for improving organisational AI literacy and education at all levels. The challenges include literacy amongst the boards and leadership team at the strategic level. A more concerning observation noted by experts is a reservation amongst internal technical teams on AI solutions. This can be explained by two factors: their limited experience with AI applications (relative to the depth and scope of experience of the experts on multiple projects) or concerns about perceived technical limitations and cybersecurity risk exposure. The experts maintain that they often have more difficulty in greenlighting a project at this level than any other. They believe that it is very difficult for an internal technical team to keep their knowledge and skills up to date relative to an external strategic partner given the current rapid rate of AI advancement.

In terms of effective proof of concepts (PoC) experts discussed the importance of rigorous and methodological design, implementation, and experimentation with PoC, as well as careful mentorship and strategic partnerships throughout the experimentation process. Furthermore, customers need to experiment with different technologies and solutions, and eventually building and experimenting with cross apps that combine multiple systems. Key challenges that are being faced with PoCs include unrealistic metrics and the more common problem of AI applications not working as well in the real world as it did in the pilots. Often, it’s an issue that the AI did not encounter in its training and requires further development to improve reliability. It is at this point that there is a high abandonment rate where organizations are disappointed with operational
improvements or accuracy or reliability and are ‘not willing to go the extra mile’. However, the experts concede that this is not an unrealistic action that organisations take. Finally, they suggest in building a tolerance for short-term tradeoffs, such as between efficiency and accuracy. Experts see an important role for organisations to be a more integral part of the future development of AI technologies. The following quotes illustrate expert opinion on enablement factors:

“Showing a proof of concept is very easy. But productizing something that works in the wild is still a Herculean effort.” (E4)

“It can be hard to get a direct ROI on AI. They’re often not willing to invest if the immediate returns aren’t there.” (E8)

“Be reasonable you need to treat AI as a junior employee, you need to nurture them.” (E10)

4.5. Nature of Work

Themes on the nature of work focused on three key areas: overcoming staff feelings of being devalued, the importance of building human capability and rethinking work design that incorporates reimagined human-machine teamwork. All the experts identified staff feelings of being devalued in their work as a key challenge that organisations are facing. Several experts identified that resistance to AI often stems from what they called an identity problem. However, experts noted that this also occurs in the reverse – many people feel empowered by AI technologies in the workplace. One important observation made by the experts is that organisations always have a choice in terms of how this is framed in language and actions to reflect their views of the value of humans over machines; the fault is not in the AI technology but in how organisations use it.

In terms of importance of building human capability, all experts agreed on the importance of ongoing capability, skill and education development for humans, and that this will need to keep pace with technology developments. Several experts maintain that the onus will be on individuals to drive their capability development as organisations tend to not keep pace. Mention was again made of generative AI tools like ChatGPT which became popular on the initiative and drive of individuals who were curious or ambitious. However, on a general level the loss of artistic, design and coding jobs were mentioned as an example of unexpected impacts of AI technologies as not long ago these jobs were thought to be safe. The framing of capability development was divided in three areas: (a) humans need to now focus their work on partnering with AI and focus on areas tasks where AI is still suboptimal, (b) people need to retrain in another field altogether as less humans will now be required in this space, and (c) AI democratizes these capabilities as it lifts skills in art, design and coding of the average person. Experts were divided whether there will be a zero-sum effect (losses of human jobs will be balanced by new jobs created), however the majority believed that there will be an overall negative effect (more jobs will be lost than created). All maintained however that no one knows for sure as its all speculation. In terms of reimagined human-machine teamwork all the experts agreed about the exciting developments collaborative work between humans and AI, particularly in areas where AI on its own is unlikely to replace humans over the short to medium term. For example, experts noted that in deploying more complex AI technologies human oracles are used to supervise certain types of machine learning algorithms that require human judgement, or when dealing with sensitive or incomplete data.

Experts maintained that it’s very important to train the human judge or oracle in any given profession on how to work with AI and in understanding how machine learning works. An example was given where a human doctor or air traffic controller needs to have a high-level understanding of the process of machine learning and fitting out of data models. Therefore, a certain level of machine learning literacy will become as essential as computer skills did 30 years ago. The overarching points that were made is that the impacts of AI will be significant, but in different intensities and timescales for each industry. A mix of quotes for this cluster is provided below:

“Certain jobs will be redundant, new ones created, but for a lot of jobs people will feel less important - and I’m talking prestigious jobs like doctors and lawyers that had elitist standings in society.” (E7)

“We have all seen the impact on the creativity with people using generative AI. You give people a tool and the freedom to do what they want, with just some limits of course, and their creativity and productivity explodes.” (E6)

“We can do a better job when we look at collaboration with AI and wherever human agency is getting compromised.” (E5)

5. Discussion

The objective of this research was to investigate organizational experiences with AI technology in response to findings in extant literature of challenges in realizing AI’s full potential (Pumplin et al., 2019; Shollo et al., 2022; Mikalef & Gupta, 2021). In our research question we asked: What are the current challenges with business adoption and implementation of AI? Our research found the prevalence of
formidable **macro-external factors** pose significant barriers to more proactive action on AI adoption; an issue that has been understated in the literature we had encountered. Whilst the literature has acknowledged the unstable and rapidly shifting economic, regulatory and technological landscape (Wagner, 2020; Collins et al., 2021) our interviews show that organisations need to practice more advanced strategic foresight. The challenges that this is creating is explained by BTF as **uncertainty avoidance** where organisations take a risk averse approach towards AI adoption in highly uncertain and rapidly changing environments resulting in that action that is short-term and predictable.

**Technology factors** identified in the interviews align with the literature in terms of a lack of sufficient technology maturity and value destruction propensity which create barriers to adoption. AI development is still hampered with critical limitations in transparency, accuracy, reliability and ethics (Seeber et al., 2020; Fügener et al., 2021). In BTF terms, this has resulted in ‘firms not optimizing but sufficing’ through short-term solutionism and with many PoCs not extending beyond the experimental stage inhibiting long-term transformation. Similarly, **enablement factors** in our research reveal the complexity of issues at create implementation friction across multiple operational areas and are usually where PoCs face major blockages. Through the lens of BTF, this can be explained as organisations affected by a perpetual state of quasi-resolution of conflict between the complex heterogeneity of issues identified in our 19 categories each with their own unique goals and challenges. Related are issues in relation to the **changing nature of work** where these challenges are attributed to insufficient attention been paid to human and workplace factors in AI development and implementation (Fügener et al., 2021; Seeber et al., 2020). Managing concerns over loss of identity, being devalued, deskilled, while enhancing human capability and reinventing human-machine collaborative systems is an under-explored source of productivity improvement and innovation as attention tends to be focused on the technology. As one expert mentioned, only 30% of their clients are interested in human issues.

Our final category of **strategy and leadership** appears as the lynchpin amongst these challenges and is dominated with what appears to be risk averse, fragmented and lacking in strategic focus. Our study suggests that an AI-transformed organization requires leadership to be more proactive in navigating complex and ambiguous technical and investment environments. On a tactical level, it needs to be more proactive in a longer-term investment strategic foresight built on a series of accumulated shorter-term experiments and PoCs for both learning and capability building. The challenges identified in our study aligns with extant literature that suggests that there are significant opportunities for improvement to better enable the benefits of AI through focused leadership, capability building, and coordinated enablement that may go beyond established drivers of digital transformation (Berente et al., 2021; Dwivedi et al., 2021. The findings may also in part explain the mixed AI performance results identified in extant literature (Collins et al. 2021; Mikalef & Gupta, 2021). Given the findings of this study, we offer the following conceptual model of the key building blocks in managing and navigating the challenges of organizational AI adoption and implementation:

![Figure 1. AI adoption conceptual model.](image)

In this model we have illustrated the interrelatedness and interdependence of the five key clusters arising from our research which highlights the ubiquitous influence of macro external factors. As this model is one of theorizing on organisational capability and performance, we also integrated dynamic capabilities of the firm theory (Teece, 2007). The additional perspective of microfoundations further extends our model by underpinning our thematic clusters: (A) **Strategic direction** supports our clusters of macro environment and strategy and leadership; (B) **Alignment capabilities** underpin the operational clusters of technology, enablement and the nature of work to achieve performance objectives; and (C) **Building organisational microfoundations**, supports capabilities required to adapt to the demands of dynamic technological and economic environments. Our model provides a theoretical perspective of AI adoption and implementation as a process by which a firm can navigate the enablers and the barriers.

We make a contribution to theory in several areas. First, we offer a means to theorize the reasoning behind how organizations make investment decisions to adopt AI technologies, and the mechanisms that
affect implementation and subsequent performance. Our contribution utilizes the lens of the behavioral theory of the firm to interpret and potentially predict organisational adoption and implementation of AI technology, and in doing so addresses calls in information systems research in this regard (Berente et al., 2021; Dwivedi et al., 2021). We also build on related work in the domain that goes beyond focusing on the AI technology to argue that organisational strategic positioning can be of more critical importance (Yun et al., 2019; Haefner et al., 2021).

We also responded to calls of Mikalef & Gupta (2021), Shollo (2022) and Pumplin (2019) for a deeper investigation on the failure of organisations to realize the potential of AI technologies. The contributions of our work has extended the basis of the theorization that organisations need to navigate a complex set of heterogenous factors to enable AI adoption and value creation. This has enabled us to theorize that low AI adoption rates and low returns on investment appearing in extant literature (Pumplin et al., 2019) may also be partly explained as an outcome of the wider contextual and thematic issues identified in our study. We also contribute to extending the BTF literature in emphasizing the significance of external factors in the macro environment of organizations in influencing their decision-making. We build on previous work in this regard (Walgrave & Gilsing, 2023; Gavetti et al., 2012) that indicate activities such as foresight and anticipation of future trends are largely missing from this theory. This has enabled us to enrich BTF by offering a more detailed understanding of macro external factors that need to be monitored and contingencies developed to help support organisations in developing a better sense of an uncertain future driven by the development of AI. This can also include theorizing about AI beyond being a traditional technology input towards the consideration that AI may in fact an economic actor that has made a complex world and organisational decision-making even more complex (Menz et al., 2021; Wagner 2020).

Our contribution also extends to theorizing on the importance of multidisciplinary approaches to understanding the complex phenomenon of AI in IS research by incorporating organisational and management perspectives and approaches. We do this by integrating the theoretical approaches of BTF in our analysis and Teece’s (2007) theorem on microfoundations in building a holistic perspective into our conceptual model (Figure 1). This builds on recent calls in the IS field (Berente et al., 2021; Dwivedi et al., 2021) for multidisciplinary approaches, that build our socio-technical tradition to proactively inform other fields and become the reference discipline for managing AI.

6. Limitations

There are several limitations to our study. The first is related to the number of experts that were interviewed. Despite the fact that it is within the methodological accepted limits as per Creswell and Creswell (2018) a greater number of experts, from a broad range of industries and geographies may have yielded a richer source of data for our analysis. A second limitation is that while every care was taken to not be overly influenced by our prior work in this domain particularly when it comes to the coding and clustering of the data, as well as its interpretation from a socio-technical perspective, we propose that our analysis, like all qualitative research may have been subject to researcher bias. Finally, the selection of technology advisors, consultants and providers for the expert interviews can also be considered a limiting factor given the specialized knowledge unique to this group. We appreciate that this could have been extended by conducting an additional set of ten expert interviews from organisations then comparing these results with the findings of this study for congruence. We note this as an opportunity for further research.

7. Conclusions

Organisations are currently operating in a time of economic, technical and social transition that is rife with conflicting information and rapid change that is framing their decisions to adopt AI technologies. Decision behaviors identified by our experts that align with BTF indicate elements of sufficing but not optimizing, short-term reactions, uncertainty avoidance, and continuous organisational learning. However, this behavior can also be seen as a legitimate response to a technological landscape characterized by hype and instability, mixed AI performance results, and critical long-term consequences of AI adoption need to be negotiated. It is tempting to view these factors as a limitation of current organisational leadership, however, they can also be explained as measured responses in an environment that is becoming increasingly destabilizing and unpredictable despite the expansive potential opportunities for value creation. This places the caliber of strategic decision-making and the skillful enablement of AI technologies as the key differentiators in organisational performance and competitive advantage rather than the AI technology itself.
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