Artificial Intelligence in the Workplace: Implementation Challenges and Opportunities

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Abstract

The augmentation of human capability with artificial intelligence is integral to the advancement of next generation information systems yet we have limited understanding of how organisations can translate the potential of AI into creating business value. We conducted a pilot study of direct users of AI enabled technologies to investigate the challenges and opportunities of successful implementations of human-machine systems. Our study found that organisations have realised positive benefits from AI projects through high levels of communication, stakeholder consultation, problem management, ethics, and transparency. Significant work is required in managing staff motivation and empowerment, trust in AI technologies, and managing novel cyberthreat issues. Shortcomings in AI technology development in the areas of accuracy, reliability, trust, and human-machine interaction appear to be significant barriers to adoption and performance, as is the integrative and synchronous development of both human and technical systems. Performance outcomes may be equally dependent on how well organisation can strategically use AI to adapt, integrate and renew itself in a constantly shifting technological landscape.

Keywords

Augmented intelligence, human-machine collaboration, information systems, AI technology acceptance.

Introduction

The augmentation of human capability with artificial intelligence is integral to the advancement of next generation information systems that drive performance improvement and innovation (Duan et al. 2019; Dwivedi et al. 2021; Berente et al. 2021). Yet we have limited understanding of how organisations can translate AI potential into creating business value through human-machine systems. Recent studies suggest that organisations are falling short in realizing business value from AI (Shollo and Müller 2022; Pumplun et al. 2019) and at best it was found to have shown mixed results (Langer and Landers 2021; Cubric 2020). To delve deeper into this phenomenon we conducted a literature review (Raftopoulos and Hamari 2023) and reviewed several studies to understand the factors that may influence performance extraction from AI technology. We found that there are four broad categories of interdependent variables at play: (1) *Human factors*, such as AI identity threat (Mirbabaie et al. 2022), personality types and trust (Schepman and Rodway 2022) and agency (Newman et al. 2019), (2) *Management factors* such as manager attitudes, technology acceptance and technology trust (Cao et al. 2021; Suseno et al. 2022), management systems (Metcalf et al. 2021), (3) *Organisational factors*, such as firm level capability (Mikalef and Gupta 2021), and entrepreneurial orientation and operations (Dubey et al. 2020), and (4) Technological factors such as algorithmic behavior (Carroll et al. 2019; Stowers et al. 2021), and issues with data model curation and machine learning (Chen et al. 2018; Crandall et al. 2018; van den Hoven 2007; Scheuerman et al. 2021). These factors provided a wide-ranging insight into the potential variables but little in terms of unequivocal findings on how AI technologies affect workplace technology acceptance and organisational performance. Several studies also suggest that performance may be context specific and therefore may not be generalizable across different AI technologies and application domains (Cubric 2020) which adds further challenge to our research focus. To build our understanding of how organisations can utilise the potential of AI to create business value we conducted a pilot study as a prelude to a larger empirical research project, to investigate the challenges and opportunities of implementations of human-machine systems focusing on the views of staff working directly working with AI enabled technologies in the workplace. Our guiding research question was: *to what degree can congruence or incongruence in the technological frames of organisational stakeholders affect AI technology acceptance and performance*? The objective of this study is to identify a more nuanced understanding of how AI technology is perceived by workers at the frontline of AI implementation and how this may affect AI acceptance and performance.

Theoretical background

The analytical framework we used for the study was technological frames of reference theory (TFR) which offers a systematic approach for examining the underlying assumptions, expectations and knowledge that people have about technology (Orlikowski and Gash 1994; Wang et al. 2021). Rooted in social cognitive research, TFR maintains that different stakeholder groups (for example, between managers and non-management staff) will hold differing views or framing of the technology under investigation and are either congruent or incongruent. Where incongruence occurs between different stakeholder groups, organisations are likely to experience difficulties around the development, implementation, and utilization of that technology (Orlikowski and Gash 1994) which limits its value creation potential.

The Technology Acceptance Model (Davis 1985) and the Unified Theory of Acceptance and Use of Technology (Venkatesh et al. 2003) are extensively employed in existing IS literature and had influenced our work, however few studies use these theories for the behavioral intention to use products that explicitly incorporate AI (Gansser and Reich 2021). We were also cognizant of the potential significance AI technology acceptance issues that go beyond the utility of the technology into complex psycho-social factors that affect the performance such as fear (Cabrera-Sánchez et al. 2021), AI Anxiety (Oh et al. 2017), algorithm aversion (Dietvorst 2015), bias and mistrust (Ishowo-Oloko et al. 2019) and wilful lack of co-operation (Kiesler et al. 1996). Our objective was to develop a more nuanced understanding of the multi-faceted nature of AI technology acceptance and organisational performance, particularly in an era where AI technologies and user perceptions of them are constantly changing and evolving. The TFR framework enabled us to consider the degree of alignment between the technological frames held by different stakeholder groups within organizations as a potential construct that identifies barriers, enablers and emergent issues for workplace AI enablement and digital transformation.

Methodology

We developed an online survey and our methodological strategy was to recruit a specialist group of employees from large organisations with direct experience in using AI technologies from Prolific.co (an online research platform that recruits screened participants for research studies). To assess respondent eligibility, we had to conduct two screening exercises due to the limitations in identifying and assessing what proportion of the candidate pool directly used AI technologies at work. In the first screen, we applied Prolific's inbuilt profile screeners to narrow down the focus on those *most likely* to be using AI at work: professionals who work full time in large organisations who have a high use of technology from their total pool of 118,449 candidates; from this we were able to reduce the eligible candidate pool at Prolific.com to a custom allow list of 8,835. In the second screen a short questionnaire was developed to assess candidates' AI technology use at work without asking any leading questions that may identify the nature of our study. This was sent to the 8,835 potential candidates and as we had time and budgetary restrictions, we selected the first 300 responses received. From this screened candidate pool of 300 we identified 132 eligible candidates who met the qualifying condition that they directly used AI technologies at work on a frequent basis. Next, we sent our detailed online survey to this group of 132 pre-screened candidates and 72 (54%) returned completed surveys in the time we had allocated. Our detailed survey consisted of twelve questions which we derived from our literature review on the key enablers and inhibitors of AI technology acceptance and organisational performance (Raftopoulos and Hamari 2023). The questions included eight multiple choice questions on AI performance, benefits, challenges, user acceptance, consultation, ethics, transparency, and personal empowerment. The survey also included four open ended questions on (a) how AI technology can be better developed and implemented, (b) The impact of AI technology on the future of productivity and innovation, (c) Consideration of AI as a viable collaborator and team member, and (d) Concerns about the future of AI for society. These questions were informed by the extant literature review on the enablers and barriers to AI technology acceptance, implementation, and performance.

Informed by TFR theory, respondents were segmented into two categories to investigate congruence or incongruence in beliefs and perceptions in relation to our research focus. Respondents self-selected which category they best belonged to; technology professionals (35% of respondents) or management professionals (65%). A statistical analysis was run on the multiple-choice questions and a thematic analysis was undertaken on the open-ended questions by using inductive content analysis (Kolbe and Burnett, 1991). In our data extraction the key themes emerged inductively by systematically interpreting the meaning and relevance of the respondents' answers to our specific research question. We took a socio-technical systems (STS) approach to our research and acknowledge that we were influenced by the core tenets of STS architecture of leadership, people, technology, structures, environment, and goals and tasks in how we coded and analyzed the survey responses. The most important area of the thematic analysis was in coding and categorising the open-ended questions into positive, negative, or conditional statements. Our approach was as follows: To the question of *'Would you consider AI as a genuine and viable collaborator and team member compared to a human?'* a positive answer would be: "yes, I do already"; a negative answer would be: "never, it's not possible"; and a conditional answer would be: "yes, but only if I could trust it". We analysed the data by segmenting and comparing the two stakeholder groups for congruence or incongruence. The demographics of the two groups are outlined in Table 1:

	Group 1: Technical staff (G1)	**Group 2: Management staff (G2)**
Respondents #	25 (35%)	47 (65%)
Median age	33 years	37 years
Age range	23 – 56 years	25 – 61 years
Gender – male #	19 (76%)	27 (57%)
Gender – female #	6 (24%)	20 (43%)

Table 1. Demographic profile of respondents by group

The demographics of both groups were similar in terms of median age and age range. There was a significant dominance of males in the technical group relative to the management group. A broad range of AI technologies in use were reported, and the majority of core functional areas of the AI technologies in use were in Information Technology (16%), Information Systems (13%), and Marketing and sales (18%) as depicted in Table 2. In terms of the core function of the AI technology, the largest categories were in customer service (21%), forecasting and prediction (17%) and optimization (16%).

Functional Area breakdown		**Core Function breakdown**	
Customer service	21%	Marketing and sales	18%
Forecasting and prediction	17%	Information technology	16%
Optimization	16%	Information systems	13%
Business analytics	9%	Human resources	9%
Diagnosis	9%	Finance	9%
Segmentation and profiling	7%	Logistics	7%
Scheduling	6%	Production	5%
Risk assessment	4%	Management	5%
Surveillance	4%	Design	1%
Cybersecurity	4%	Other	17%
Other	2%		

Table 2. AI implementations profile: Functional Area and Core Function

Results

There was a striking consistency in the results of both employee segments in terms of positive ranking and perceptions across the five areas of AI technology performance, user acceptance of AI technology, and satisfaction with the levels of consultation, management transparency and ethics offered by their organisations. For example, this level of congruence can be illustrated by the question in relation to how well the AI technology has performed in Table 3 where the majority of respondents similarly indicated that AI performed either very well or extremely well. It is also noteworthy that despite a lack of negative ratings, a significant proportion of both groups were still neutral citing early days of the implementation:

	Group 1: Technical staff	Group 2: Management staff
Extremely well	12%	15%
Very well	59%	58%
Neutral	29%	28%
Not very well	0%	0%
Poorly	0%	0%

Table 3. How Well Has the AI Technology Performed

The reasons cited for the positive performance of the AI technologies were process improvement, time, accuracy and efficiency. Respondents that were neutral maintained that there was still a lot of human effort required to manage the AI technology, that a high degree of human and resource effort was needed to train the AI (machine learning), the high financial cost of the AI investment and implementation, and that they were still in a proof-of-concept stage of the implementation.

How can AI be Better Developed and Implemented

Respondents were asked an open-ended question about how AI technologies can be better developed and implemented in their organisations. Using a thematic analysis, we categorised their responses according to the four thematic clusters: strategic, technology, systems, human and other. Examples of the key abridged responses that emerged for each cluster and by stakeholder group are as follows in Table 4:

Overall mentions	**G1 Responses example**	**G2 Responses example**
Strategic issues G1=20% G2=19%	Organisational education Involve researchers Legal caveats clarified	Research and user testing Knowledge transfer More use cases needed
Systems issues G1=24% G2=21%	Integrate into processes Stakeholder consultation Process re-engineering	Multi-discipline teams Expert change facilitation Human override in decisions
Human elements G1=4% G2=13%	Human requirements focus Human interaction focus AI interface improvements	User feedback sought Reduce complexity for users Human like AI responses needed
Technology factors G1=40% G2=32%	High quality data Data clarity & transparency Data management environs	Remove AI bias Lean development techniques AI technology synergies
Other G1=12% G2=15%	I don't know	Not sure/no idea

Table 4. How Can AI Technology be Better Developed and Implemented

Technology-related factors formed the most significant category for both stakeholder groups on how AI can be better developed and implemented (G1=40% and G2=32%). The key issues focussed on the access, curation and management of data, AI bias, lean development, and developing AI technology synergies with legacy IT and IS systems. The two other significant thematic clusters of strategic and systems issues focused on integration and transformation issues common in key technology implementation programs.

AI Impact on Sense of Personal Empowerment

In terms of feelings of personal empowerment in their jobs, most respondents only felt moderate levels of empowerment (G1=53% G2=71%), however technical staff overall were more likely to feel very or highly empowered than management staff (G1=38% G2=18%). An interesting observation is that despite the high levels of positive perception of AI performance and acceptance, most respondents still feel a sense of disempowerment in their roles as AI implementations expand.

AI Impact on Productivity, Collaboration and Innovation

When considering the future impact of AI on workplace productivity, collaboration and innovation, most respondents made positive statements (G1=52% G2=55%), a sizeable proportion made conditional statements (G1=40% G2=28%) only 10% made negative statements (G1=4% G2=13%) and a small proportion maintained that they didn't know. The key themes that emerged are as follows:

Overall mentions	**G1 Responses example**	**G2 Responses example**
Positive statements G1=52% G2=55%	It will have a huge impact AI will be a common tool More potential to come	Great to augment human skills Automation good in particular Frees up time and resources
Conditional statements G1=40% G2=28%	Needs to be used correctly Only if implemented well Good but limited potential	Promising but still limited Can't yet trust it Good but still needs supervision
Negative statements G1=4% G2=13%	It's only useful as a tool It is still severely biased Can't match human skill	AI is no match for humans Hardships and job losses Not for creative tasks
Don't know G1=4% G2=4%	I don't know	I don't know

Table 5. Impact of AI on the Future of Productivity, Collaboration and Innovation

While most respondents support the positive potential and role of AI technologies in the workplace, they are also cognisant of the need for improved technology development and implementation. Both stakeholder groups hold the perception that the current capabilities of human-machine collaboration tools are still sub-optimal in areas of trust, performance, and implementation.

AI as a Collaborator and Team Member

When considering AI as a viable workplace collaborator and team member, both groups were consistent with negative statements (G1=44% G2=45%) citing critical limitations in AI capability to replicate innate human skills as well as limited trust in the technology's performance. It is interesting to note that both technical and management staff share the same negative and conditional sentiments that appear to be anchored in socio-emotional-cultural issues around the importance of humanity, the innate or irreplicable human contribution to workplace collaboration and teaming, and that AI is just another technological tool. Clearly from the conditional statements we can see in Table 6 that despite the perceived positive potential of AI there are several technical and development hurdles that need to be overcome such as trust, reliability, anthropomorphism, and accuracy to advance human-machine augmentation potential.

Overall mentions	G1 Responses example	G2 Responses example
Positive statements G1=12% G2=4%	Faster, reliable decisions Input without emotion Helps humans work smarter	Great, fast decisions Already part of the team Convinced of the benefits
Conditional statements G1=40% G2=45%	Natural communication Pass the Turing test More accurate forecasting More development needed Not possible at the moment Develop self-awareness	Needs to be trustworthy Sentience More human-like More reliability Fail safe - which isn't possible It still feels robotic
Negative statements G1=44% G2=45%	Human team member is irreplaceable AI is a tool not a team member AI is just an enabler	I'll never consider it Human beings are irreplaceable AI is no substitute for humans Won't happen any time soon
Don't know G1=4% G2=6%	I don't know	I don't know

Table 6. What Would it Take to Consider AI as a Viable Collaborator and Team Member

In prior questions respondents were aware of the benefits and limitations of the AI technologies in their workplace. However they were particularly critical of in relation to the idea of human-machine teaming and collaboration citing critical limitations in the current suite of AI technologies. This is consistent with extant literature on this topic on the current irreplaceability of human capability on more complex tasks and ambiguous problem spaces (Akata et al. 2020; de Cremer et al. 2021; Demartini et al. 2016).

Concerns about the future of AI in Society

In terms of concerns about the future of AI in society, key themes emerged in five key areas of cyberthreats, job losses, ethical concerns, and loss of humanness (see Table 7). Key areas of incongruence between the stakeholder groups were that technical staff were nearly twice as likely to cite cyberthreats as a concern (40% compared to 21%) and conversely, management staff were more likely to express loss of humanness (G1=12% G2=21%) and no concerns (G1=16% G2=26%) compared to technical staff.

Overall mentions	G1 Responses example	G2 Responses example
Cyberthreats G1=40% G2=21%	AI terrorism, hacks, scams Unsupervised AI errors Bad AI configuration	Release AI before its ready Technology in the wrong hands Cyber security
Job losses G1=24% G2=28%	Reduction of human jobs Worker displacement Loss of human skills	Job losses Human redundancy Lost livelihoods
Ethics concerns G1=8% G2=4%	Invasion of privacy Military usage of AI Biased datasets	Security concerns Technology ownership/control AI bias & trust
Loss of humanness G1=12% G2=21%	Inauthentic experiences Loss of common sense Working with algorithms	Loss of empathy & compassion Overreliance on AI Human substitutes
No concerns G1=16% G2=26%	AI is not the problem, humans are; no concerns	I don't think AI will be that impactful; I have no concerns

Table 7. Concerns about the future of AI in society

Discussion

Our guiding research question was: to what degree can congruence or incongruence in the technological frames of organisational stakeholders affect AI technology acceptance and performance? We have used technological frames of reference theory (Orlikowski and Gash 1994; Wang et al. 2021) as a high-level approach for examining the underlying assumptions, expectations, and knowledge that management and technical stakeholders have about AI technology in their organisations that may inform change management practices for AI enablement. We found that there was a high level of congruence (or similar views and framing of workplace AI technology) on a positive acceptance of AI technology and on a recognition of AI value-adding performance. Furthermore, both stakeholder groups had articulated a similar set of perceived barriers to AI acceptance and performance, however they appear to be anchored from a position of constructive criticism rather than fear or anxiety. This is illustrated in the context of the congruent responses claiming that AI technology is not yet ready, reliable, and trustworthy in areas that require high levels of human-machine teaming and collaboration in decision-making.

The perspective of this group of respondents is that the performance of augmented AI technology is still sub-optimal at this point in time. From a TFR perspective, this indicates a high level of alignment on staff perceptions of the elements that enable value creation as well as elements that limit current or future value creation (or even destroy value). The high level of congruence between the views of both stakeholder groups suggests that there are wider socio-technical implications that need to be considered, rather than just focussing on the role of the user. From a theoretical perspective, technological frames are shaped by different antecedents such as (1) personal attitude, (2) application value, (3) organizational influence, (4) leader influence, and (5) industry influence (Spieth et al. 2021). Our findings suggest that these areas provide the potential microfoundations for building more effective organisational capability in AI enablement, which raises additional challenges for technology and systems designers.

Several systemic socio-economic issues were mentioned by respondents as perceived barriers to AI technology acceptance and performance. For example, cyberthreats and job losses represent wider socio-industrial-economic origins and consequences, and perceived loss of humanness speaks to the systemic socio-cultural implications of the unknown emergent society that will evolve. However, despite these issues being commonly perceived as being out of the control of organisations, the implications for practice are that organisational leaders can take a more proactive approach in terms of systems design and the development and communication of unique organisation values and polices to counteract the potential negative impact of AI on their workforce. As our survey shows, staff appear to be showing positive goodwill to enable AI despite an uncertain future for their personal empowerment and job security.

Several findings have implications for practice and opportunities for further research. The significant percentage of 'no concerns' in relation to the future impact of AI technologies (Table 7) offers two possible hypotheses: (a) a limited awareness of the issues given that this category was dominated by non-technical staff, and/or (b) staff at the coal face of AI implementations may in fact have a higher level of awareness of the workability issues of AI technologies than organisations and developers give them credit for. A close inspection of the responses and sentiments suggests that respondents to our pilot study were not overtly complicit in the AI hype that is often a criticism of the industry, and in particular the exaggerated media reporting of AI technologies (Marcus 2022; Newlands 2021). Implications for practice is a need for open communication, staff training and critical research as a basis for more informed strategic decision making on AI investment. Concerns over the loss of humanness (Table 7) highlights the importance of the relational and experiential needs of humans in the workplace (and society as a whole) and how organisational leaders manage this important transition.

This raises opportunities for improvements in a wide range of issues that were mentioned by respondents in the areas of human-machine interaction, AI interface design, and workplace and systems design – elements that focus on human empowerment and motivation as this is still a key driver of organisational productivity, creativity, and innovation. Both human and machine systems need to be developed in tandem for the overall system to flourish. Given the widely reported incidence of mixed results on AI technology performance, acceptance or return on investment in extant literature, the insights we can glean from our pilot survey suggests that the implication for practice lies in how effectively organisations can integrate AI technology or more pointedly, how organisations can recreate new systems where the AI technology implementation introduces a stepped change in the organisations core business. Value creation from AI technologies represent unique challenges due to the complex interactions between technology, systems, tasks, and processes (Spies et al. 2020). Furthermore, human-machine systems based on generative AI technologies require a more sophisticated approach to organisational design and digital transformation than have been offered by the conventional frameworks of the past (Hanelt et al. 2020), as well as the design of task and technology alignment in workplace and functional designs (Goodhue and Thompson 1995). The implication here is that competitive or comparative advantage may not necessarily be in the investment in AI, but on how well organisations can strategically use AI to adapt, integrate and renew itself in a constantly shifting technological landscape. The high level of stakeholder congruence in our research suggests the limitations also lay in the capability and configurations in the AI technology and overall system design, rather than in the fear and limitations of human collaborators.

Conclusions

Our pilot survey suggests that organisations have realised tangible benefits from current AI projects through high levels of communication, stakeholder consultation, problem management, ethics, and transparency. There appears to be a high level of congruence between technical and management staff on these issues, which indicates positivity of staff towards of working with AI in a constructive manner. In our sample, respondents reported widespread agreement on positive technology acceptance and success of AI implementations which runs counter to much of the literature we have reviewed on this issue. However, our survey has also revealed significant congruence on key operational and implementation issues that provide opportunities for further research. Organisations can be doing more to alleviate concerns over job losses, and loss of humanness in the workplace as AI technologies continue to advance. Significant work needs to be undertaken in managing staff motivation and empowerment, trust in AI technologies, and managing of complex and novel cyberthreat issues. Shortcomings in AI technology development in the areas of accuracy, reliability, trust, and human-machine interaction appear to be significant barriers to adoption and performance, as is the integrative development of human technical systems as a synchronous whole. Our findings highlight these factors as essential microfoundations for successful human-machine system implementations that require further investigation and research in organisational capabilities development as an integral component of future AI development.

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