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Research Article

Technology readiness and the organizational journey towards AI adoption: An empirical study

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ABSTRACT

Artificial Intelligence (AI) is viewed as having potential for significant economic and social impact. However, its history of boom and bust cycles can make potential adopters wary. A cross-sectional, qualitative study was carried out, with a purposive sample of AI experts from research, development and business functions, to gain a deeper understanding of the adoption process. Technology Readiness Levels were used as a benchmark against which the experts could align their experiences. A model of AI adoption is proposed which embeds an extended version of the People, Processes, Technology lens, incorporating Data. The model suggests that people, process and data readiness are required in addition to technology readiness to achieve long term operational success with AI. The findings further indicate that innovative organizations should build bridges between technical and business functions.

1. Introduction

Technological advances, particularly in machine learning (ML) and robotics, coupled with the availability of big data and technology to exploit it, have led to optimistic predictions (that some might call hype) about the economic potential of AI. Policy makers are backing the technology with AI initiatives (MOST (Ministry of Science and Technology) P.R.China, 2017; UK Government, 2019; US Government, 2021). Applications of AI are being actively investigated, e.g. in healthcare (Joshi & Morley, 2019; Leone, Schiavone, Appio, & Chiao, 2021), recruitment (Kim & Heo, 2022), law (Volokh, 2019), logistics (Woschank, Rauch, & Zsifkovits, 2020), and government (Zuiderwijk, Chen, & Salem, 2021). While there have been some indications that the level of investment in operational systems is less than the hype suggested (Alsheibani et al., 2019a; Gartner, 2017; Sjödin et al., 2021; Willcocks, 2020), McKinsey report 50 % of respondents to one survey having deployed AI in at least one function, albeit with a substantial divide between investment levels in technology leaders and other firms (McKinsey, 2020).

The definition of AI is unclear (Berente, Gu, Recker, & Santhanam, 2021; Collins, Dennehy, Conboy, & Mikalef, 2021; Duan, Edwards, & Dwivedi, 2019). This lack of clarity may be explained by the multidisciplinary nature of AI research, as well as growing business and public interest in the subject which bring together multiple perspectives. In this paper, we adopt DeCanio (2016) technology-neutral definition of AI as *"the broad suite of technologies that can match or surpass human capabilities, particularly those involving cognition"*. We choose this definition for its breadth and its practical focus over others, such as McCarthy (1958) "*the science and engineering of making intelligent machines*", because, while for some applications like chatbots, mimicking actual human behavior is needed, in many cases the aim is to produce benefit for the organization deploying AI, through automating or supporting capabilities such as decision making, which would otherwise be provided by the human workforce.

It is helpful to scope our discussion of AI applications in terms of technology and applications to which it can be applied. ML technology is driving the current AI spring (Collins et al., 2021) but Toorajipour, Sohrabpour, Nazarpour, Oghazi, and Fischl (2021) found that artificial neural networks, although the most common AI technique, were used in less than 30 % of supply chain management examples. AI is thus better seen as a suite of enabling technologies, which may be brought together to provide autonomous applications that have practical benefits. Uren (2020) identifies learning, perception, reasoning, communication and knowledge representation as the technology categories found in AI, while Collins et al. (2021) list expert systems, machine learning, robotics, natural language processing, machine vision and speech recognition applications. Knowledge representation and reasoning, which drove the earlier AI springs, are important technologies in expert system

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and semantic web applications, while perception technologies, with their use of sensors along with machine learning to support adaption to work in changing environments, are applied in robotics. Since AI technologies are of many kinds, different technologies exist at different stages of readiness and may pose different challenges to adopters. As will be discussed further in the literature review, the concept of technology readiness was devised to describe how close a technology is to operational use. In this work, we used readiness as a measure to benchmark participants' perceptions of the progress towards mature operational deployment of AI projects they had been involved in. As the unit of analysis was the project, readiness in this study also encompassed organizational readiness (Alsheibani, Cheung, & Messom, 2018) and the socio-technical factors necessary for success.

AI cannot be adopted without collaboration between different functions of a company (Akkiraju et al., 2020) and that collaboration typically takes place in the context of an IS project. Pilot projects have been recommended as a route to adoption for organizations that are new to AI (Lahlali, Berbiche, & El Alami, 2021), but Neumann, Guirguis & Steiner (2022) describe adoption as *"an ongoing process instead of a single point in time"*. From this perspective, an isolated pilot project is unlikely to result in mature adoption. We argue that the adoption process can be conceived as a sequence or suite of projects. Therefore, the project was selected as the unit of analysis for the study, providing an anchor for conversations with experts.

The perceived scope of AI, such as fears that it endangers employment (Frey & Osborne, 2017; Goethals & Ziegelmayer, 2022) or its use in "surveillance capitalism" (Zuboff, 2019), results in unusually complex social and organizational contexts for AI adoption. Makarius, Mukherjee, Fox, and Fox (2020) go as far as to observe (p.263) that "the changes that occur with AI integration are uniquely different than those of prior industrial revolutions." Thus, AI is not just another generation of MIS to which old lessons can be applied. New challenges face adopters of AI, such as determining how much responsibility to delegate to autonomous systems (Berente et al., 2021). Information management researchers need to address these challenges by conducting empirical socio-technical research that contributes to understanding AI technology, its synergy with Big Data, and the process of adopting it (Cybulski & Scheepers, 2021; Duan et al., 2019; Huysman, 2020; Schuetz & Venkatesh, 2020). For practitioners, such research would help them to formulate strategies for AI development, identified as a gap by Dwivedi et al. (2021).

This study advances theoretical understanding of the organizational journey towards AI adoption by bringing together the perspectives of technology readiness and socio-technical factors, into an extended model of the technology adoption process which emphasizes the changing relationships between data and other factors through the adoption/implementation process. It also has practitioner relevance, by identifying socio-technical factors that facilitate AI projects.

We first present a literature review that clarifies the theoretical lenses used in the study and justifies their application to the context of AI development projects. The research methodology is then described, followed by findings concerning the uncovered need to extend the People, Processes, Technology model to include Data and to develop readiness in all four aspects. We discuss the extensions to theory that are outcomes of the study, and the implications for practice, conclusions and future directions of research.

2. Literature review

Research on the adoption of innovative information systems has followed a number of well-established approaches which Jeyaraj, Rottman, and Lacity (2006) argue can be broadly classified as those which focus on use of technology, including the Technology Acceptance Model (TAM) and its derivatives such as Unified Theory of Acceptance and Use of Technology (UTAUT), and models with an organizational perspective such as Technology Organization Environment (TOE) and stage theories. These approaches have applied in AI adoption studies, for example Chatterjee, Rana, Dwivedi, and Baabdullah (2021) combine both TAM and TOE in a study of adoption of Industry 4.0 technology (encompassing AI) and the factors identified by Khanijahani et al. (2022) in their review of health care related AI adoption studies include things like "perceived ease of use" which reference approaches derived from TAM. The TOE model has also been widely applied to examine AI adoption, e.g. (Alsheibani, et al., 2018; Pumplun, Tauchert, & Heidt, 2019; Neumann, et al. 2022; Yu, Xu, & Ashton, 2022).

Nonetheless, researchers have identified a need for new approaches to studying AI adoption, in particular taking consideration of factors related to its potential for societal impact. Chi, Denton, and Gursoy (2020) point out that current models do not adequately address anthropomorphism of service agents. Cao, Duan, Edwards, and Dwivedi (2021) developed an extension of TAM/UTAUT that factors in some of the specific societal concerns that might impact a manager's intention to adopt. Khanijahani et al.'s (2022) study highlighted perceived threat of AI to medical professionals' autonomy. Sánchez-Prieto, Cruz-Benito, Therón Sánchez, and García Peñalvo (2020) extended the TAM model to include factors such as university students' trust of AI used in assessment. This work therefore takes a socio-technical approach to examining the AI adoption process. This decision is reinforced by a thread of discussion of socio-technical themes in AI, explored further in Section 2.1.

2.1. Socio-technical themes in AI

The adoption of AI technology affects people's motivation and their ability to carry out skilled tasks effectively. In recent years, this theme has had growing prominence in the literature.

AI, like all new MIS, requires the development of improved technical skills (Achmat & Brown, 2019; Alsheibani, Cheung, & Messom, 2019a; Jöhnk, Weißert, & Wyrtki, 2021), and top management support (Alsheibani, Messom, & Cheung, 2020; Jöhnk et al., 2021; Pumplun et al., 2019) to achieve successful adoption. This has been established for several decades, e.g., Gill (1995) identified loss of developers post adoption as a cause of system failure in early expert systems. Other factors diverge from issues found in standard MIS. Schuetz and Venkatesh (2020) envision a world in which users are increasingly unaware that they are interacting with machines, but other authors stress the need for AI to become understandable to the people who carry out processes in which it is deployed, and whose roles must adapt to use it, e. g. (ICAEW, 2017; Klumpp, 2018; Makarius et al., 2020; Schidzig & Weinstein, 2017; Sutton et al., 2018).

Technical skills are not the only knowledge resources needed. Innovation teams should bring together a range of skill sets. Guillaume et al. (2014) predict positive effects on innovation with diverse teams (including functionally diverse teams) where self-efficacy is high, although diverse teams start more slowly. Sjödin, Parida, Palmié, and Wincent (2021) advocate using cross-functional teams based on six Swedish cases. Their suggested team make-up leans rather towards the development phase: "application developers, data scientists, data engineers, business developers, and business-unit experts" (p.580). Bringing in business-unit experts may be expected to bridge knowledge gaps compared to purely technical teams, such as the market knowledge identified by Ellwood, Williams, and Egan (2022) as required to get innovation projects across the valley of death ("valley of death" refers to the difficulty of getting innovative technologies beyond the prototype stage and into use (Frank, Sink, Mynatt, Rogers, & Rappazzo, 1996)).

The impact of AI on jobs and the nature of roles has been discussed widely, e.g. (Du & Xie, 2021; Frey & Osborne, 2017; Strich, Mayer & Fiedler, 2021). Although Willcocks (2020) predicts that automation will create some jobs, negative themes are prominent, such as unemployment (Frey & Osborne, 2017), changes to the nature of professional roles (Kokina & Davenport, 2017), user fears of AI (Willcocks, 2020) and technology acceptance/resistance (Cao et al., 2021; Duan et al., 2019;

Frick, Mirbabaie, Stieglitz, & Salomon, 2021). In the MIS development process, stakeholders are routinely involved out of sound user-centered design principles. In the AI literature, however, the importance of the user has often taken second place to the novelty of the technology, with honorable exceptions, e.g. (Jin, Carpendale, Hamarneh, & Gromala, 2019; Rantavuo, 2019). However, encouraging development teams to understand user fears has the potential to help organizations avoid "oppressive" scenarios such as those postulated by Kane, Young, Majchrzak, and Ransbotham (2021).

The progress of AI adoption has followed a series of "boom and bust" cycles ("AI springs" and "AI winters"). For business applications, it is generally agreed that the most substantial AI spring, until recently, was the expert systems boom of the 1980s, which had nevertheless become an AI winter by the mid-1990s after recognition that significant numbers of reported commercial applications were not in "real" operational use (Mingers & Adlam, 1989; Ovum, 1986). Gill (1995) discusses the reasons for that decline. Factors which caused specific expert systems to be abandoned included not fitting a problem that users considered significant and changes to the Management Information Systems (MIS) infrastructure. It was noted that systems which were embedded in bigger MIS were more likely to succeed. We argue that this provides a pressing reason to take account of socio-technical factors in adoption studies, since if the AI does not fit the MIS as a whole, the risk of failure is increased.

2.2. People, processes, and technology

The operational elements of socio-technical systems have been viewed as a "golden triangle" of people, processes and technology. This view has its origins in Leavitt (1964) "diamond" consisting of technology, people, tasks and structure. As a result of the growth of business process thinking in the 1990s, around the beginning of this century several authors independently proposed a version in which processes replaced the tasks and structure elements. These included Edwards (2000) and Malhotra (2000) from academia, Gongla and Rizzuto (2001) at IBM, and Massey, Montoya-Weiss & O'Driscoll (2002) at Nortel Networks.

Leavitt's work emphasized that managers need to pay attention to the interactions between the diamond's four elements, so the links between the elements are as important as the elements themselves. However, he contented himself with offering examples of possible interactions rather than attempting to capture the nature of those links in general. A significant advance in the triangle version was the addition of identified links between the three elements (Fig. 1) (Edwards, 2005).

The triangle model has subsequently become common in the IS management literature, particularly in knowledge management (e.g., Yang, Brosch, Yang, & Cadden, 2020) and cybersecurity (e.g., Parent & Cusack, 2016). It has been used in diverse application areas from policing (Gemke, Den Hengst, Van Rosmalen, & De Boer, 2021) to disaster recovery planning (Blake, Stevenson, Wotherspoon, Ivory, & Trotter, 2019). Even when the triangle model is not used explicitly, the three elements are often seen in use to structure analysis or discussion, for example in Makarius et al. (2020) when considering the issues of integrating AI systems and human employees in organizations.

The People, Processes and Technology model was considered a good fit to analyze the components of socio-technical systems in the context of AI adoption projects based on literature which supports the relevance of the component elements of the model:

- effects of AI on people (Frey & Osborne, 2017; Klumpp, 2018; Makarius et al., 2020),
- importance of processes (Saari, Kuusisto, & Pirttikangas, 2019),
- process and people factors (Coombs, Hislop, Taneva, & Barnard, 2020),
- development of people's skills (Alsheibani et al., 2019a; Kolbjørnsrud, Amico, & Thomas, 2016),
- fit of technology to business needs (Alsheibani et al., 2018; Saari et al., 2019; Tarafdar, Beath, & Ross, 2019).

It could be inferred that, in a project, the three elements might come together, for example the AI technology selected by a project team may impact the nature of tasks (Willcocks, 2020) and hence the processes to which tasks contribute. This in turn impacting on the project stakeholders (people) who are operating the processes, for example by changing the nature of their roles (e.g., Niederman, 2021). However, no study analyzing empirical evidence for this was found. The use of the model in the analysis is explained further in Section 3.

2.3. AI, readiness and maturity

Adoption requires organizations to be prepared, or ready, to take the different steps in the adoption journey. The concept of maturity has similarities to readiness, in that maturity models are typically presented as levels, the difference being that maturity research captures management issues as maturity extends through adoption and into established use of technology. Maturity can be illustrated with the Capability

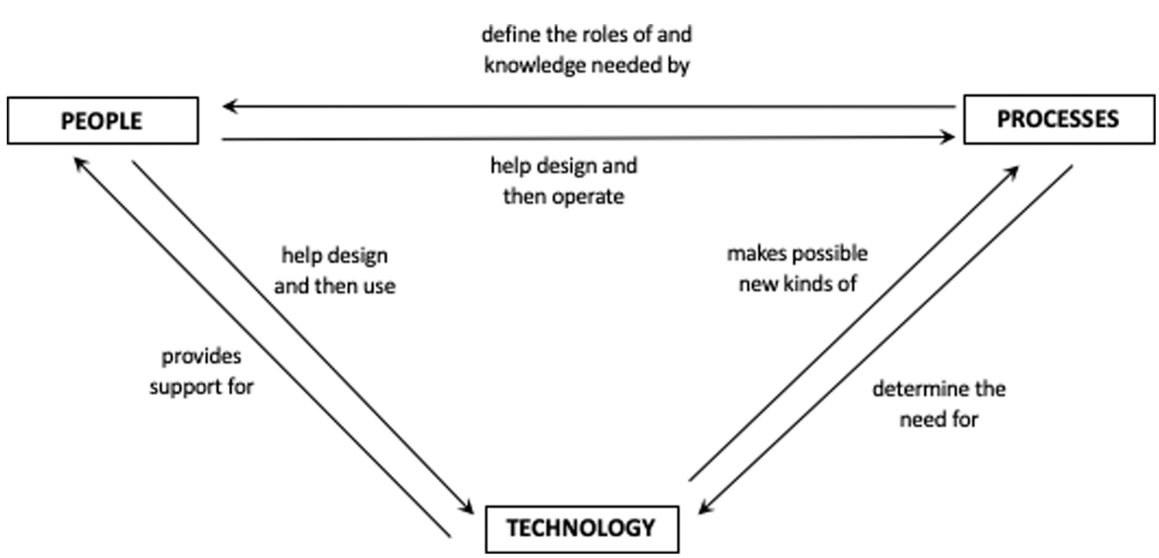


Fig. 1. People, Processes and Technology, based on Edwards (2005).

Maturity Model (CMM) (Paulk, Curtis, Chrissis, & Weber, 1993) which provides measures of organizations' ability to manage software development processes. CMM has five levels: initial, repeatable, defined, managed and optimizing. These chart an organization's progress from the ability to produce systems in an ad hoc way to quality-controlled processes.

Recent work has demonstrated interest in maturity and readiness concepts related to adoption of AI by organizations. Sadiq, Safie, Abd Rahman, and Goudarzi (2021) provide a systematic review covering fifteen AI Maturity Models (AIMM) and conclude that just half are rigorously validated, ten are designed for specific purposes, and for 80 % of the studies the scope is company and process. This implies there is a gap for an empirical study of readiness/maturity that examines the project level and is not industry specific. One theme in the literature of AIMM is to propose a maturity model, typically for organizations to assess or improve their own maturity, for example (Akkiraju et al., 2020; Ellefsen, Oleśków-Szłapka, Pawłowski, & Toboła, 2019; Pumplun, Fecho, Wahl, Peters, & Buxmann, 2021; Saari et al., 2019). This work does not presume to do that. Rather we use the readiness concept as a benchmark that allows us to identify how project teams adjust what they do depending on the level of technology readiness they are working at. This aligns with a second theme of research which uses readiness and maturity concepts to organize findings according to levels or stages, e.g. (Alsheibani et al., 2019a; Neumann et al., 2022; Zhang, Zuo, He, Li, & Yu, 2021).

To take account of the readiness concept, a measure of readiness was needed to benchmark the progress that projects had made towards operational deployment. The Technology Readiness Levels scale (TRL) was developed by NASA (Mankins, 1995) as a tool to support the management of technology development for its space programme and has since been adopted in sectors such as aerospace and energy, as well as by the European Union (Héder, 2017). The scale has nine levels, which track technologies from basic science to deployment in the operational context (see Table 1). Modifications to the wording of level descriptions have been made to fit TRL to different technology applications, including intelligent systems (Meystel, Albus, Messina, & Leedom, 2003). The relevance of TRL to AI has been demonstrated by Martínez-Plumed, Gómez, and Hernández-Orallo (2021) who have used the scale to rate AI technologies.

For the purposes of the study, the TRL provided the benchmark measure against which the expert participants could place situations that had occurred during projects.

In summary, the readiness approach is an important component of AI discourse because it illuminates adoption as a process, so that we can begin to uncover factors which may explain why many organizations struggle to deploy AI beyond isolated applications, or to maintain it in use long term. In this paper, we address a gap in the studies of readiness/maturity that occurs at the level of the project. As the need for different kinds of socio-technical models to examine AI adoption has been identified, we deploy two lenses for the analysis which have been successfully used elsewhere. We use PPT because it is proven as a socio-technical model that takes in all aspects of information systems. We use TRL because AI technology covers a range of different technologies at different levels of readiness and those different levels may be associated with different socio-technical factors.

3. Methodology

This qualitative study takes TRL as a benchmark measure of the progress of AI projects towards adoption, using interview data from research, business and development participants. As the aim is to advance the understanding of the organizational journey towards AI adoption, a qualitative study presents an opportunity to explore the issues relevant at different adoption stages.

The socio-technical systems approach acknowledges the significance of the human and social aspects of technology use. From this perspective, qualitative studies, such as this one, with their assumption that *"meaning is socially constructed by individuals in interaction with their world"* (Merriam, 2002) have become established as important contributors to the development of in-depth knowledge about the interactions between different aspects of socio-technical systems. In addition, we take the work of Gregor (2006) as a guideline for theory development in MIS.

This study is cross-sectional: the semi-structured interviews were carried out in late 2019 and early 2020. The questions were designed to get participants to reflect on the issues they had faced in the context of the TRL level of the AI developed in projects. Participants were presented with a TRL scale and asked to rate the TRL level of projects they had worked on, before probing other aspects affecting the success of the projects. The unit of analysis of the study, the project, brings together both social and technical aspects of innovation. The TRL scale that was used adapted a version by Meystel et al. (2003) with diagnostic questions for each level, posed in terms that would be accessible to end users and managers as well as IT specialists. The scale is summarized in Table 1.

In particular, we probed resources needed to deliver projects, the interaction with clients, and whether the project/s had met expectations and been judged successful. This approach introduced a benchmarking element: by asking the participants to think about projects which had achieved different TRL levels they were guided to report what happened at different stages of adoption.

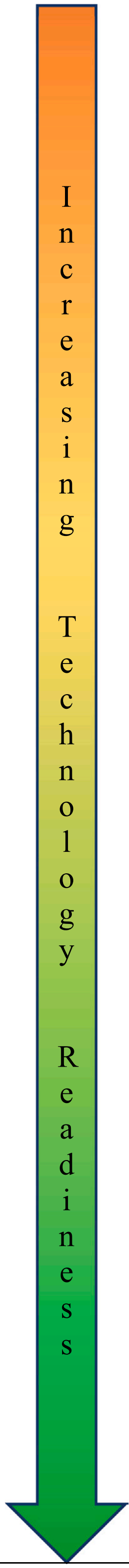
Fourteen (n = 14) interviews were carried out, with a total of fifteen participants. The criterion for inclusion was participation in AI projects with some involvement of real-world application by organizations, i.e. excluding theoretical research, but including applications based research, and knowledge transfer, in order to get a representative range of TRL levels. Participants were purposively sampled to represent a range of viewpoints from business (n = 6) development (n = 4) and research (n = 4) functions (see Table 2). These different viewpoints were chosen to represent professionals with different types of experiences of innovative AI projects in order to avoid the 'tunnel vision' that might come from only sampling one type. The number of participants was not fixed in advance. For each viewpoint, we interviewed participants until it was clear there was agreement between them on themes significant to the aims of the study, and until no new information emerged, i.e. when saturation was achieved. The mean interview length was 44 min.

A systematic approach to coding was adopted, with the aim of drawing out the socio-technical themes of the interviews based on detailed readings of the transcriptions (Thomas, 2006). The two lenses (TRL and People, Processes, Technology) were used to focus the analysis on the objectives of the study, which is identified by Thomas (2006) as differentiating the general inductive approach from Grounded Theory Method, but analysis was not constrained to testing a priori assumptions. Additional themes that emerged were data, sub-themes of processes for business (denoted by the suffix /b) and development (denoted /d), and success criteria.

All transcription, coding and analysis of interview data was carried out by the authors. Following initial familiarization, identification of themes, and coding of samples to ensure consistency, a coding manual was written with definitions and sample extracts. For example, the definition for the TRL theme read *"Based on the NASA Technology Readiness Levels with modifications for IS. Concerns the development of technology from principles and vision (level 1) through to operational use (level 9). May code the levels (TRL 1–9) that are relevant."* Examples were *"Then we do it on site with them and with real data. Typically, what we'll do is we'll do it in parallel to production."* [TRL 4 or 5] and *"The ones that get it, they go into the execution, so from probably TRL 5 through to that prototype, get the business buy in."* [TRL 5+].

Each author then coded two transcripts following the manual. The highlighted extracts were copied to spreadsheets (one per code) and sorted by coder. A comparison and discussion clarified and removed any

Table 1
Technology Readiness Level scale based on Meystel et al. (2003).



Level	Description	Diagnostic Questions
TRL 1	Basic Principles and Broad vision	Have you researched the system in principle? Do you have a vision for the system?
TRL 2	Conceptual design	Have you proposed engineering components which need to be part of the system? Do you have a conceptual design for the system?
TRL 3	Theoretical & experimental analysis. Proof of concept	Have you experimented with subcomponents of the system? Have you scrutinized innovative components?
TRL 4	Component validation in "laboratory" conditions	Have you integrated subcomponents of the AI system to check that they will work together? Have you considered issues such as interoperability, maintainability, scalability, security etc.?
TRL 5	Component validation in more realistic conditions	Have you developed a high-fidelity prototype of the system with reasonably realistic components? Have you verified the prototype works as desired?
TRL 6	Subsystem model or prototype demonstration	Have you demonstrated a prototype system in a relevant environment (e.g. lab test with realistic data or test in simulated environment)?
TRL 7	System prototype demonstration in operational environment	Do you have an operational system that can be demonstrated in its operational environment? Are there processes in place to support the software?
TRL 8	Actual system completed, tested and demonstrated	Do you have a system which is in its final form and meets its design specifications? Is it ready to work in its intended application?
TRL 9	Actual system proven through operational use	Has the software been used under operational conditions for an extended period? Has it been debugged? Does it reliably produce the required outputs?

Table 2
Expert informants on AI.

ID	Viewpoint	Notes	Country
B1	Business	Government safety engineer	UK
B2	Business	Entrepreneur, developer	Ghana
B3	Business	Consultancy, RPA, data governance	UK
B4	Business	Government, health systems	UK
B5	Business	Entrepreneur, health systems	UK
B6	Business	Entrepreneur, building management systems	UK
D1	Development	IT consultancy, a manager and a senior developer	UK
D2	Development	Software company, solution architect	UK
D3	Development	IT consultancy, developer	UK
D4	Development	AI software company	Germany
R1	Research	University professor	UK
R2	Research	Knowledge transfer project technical adviser	UK
R3	Research	University professor	UK
R4	Research	University professor	Netherlands

remaining differences in interpretation of the codes. With these quality checks complete, the full set of transcripts were coded and the process of extracting them to spreadsheets and reviewing them was repeated. Some extracts were recoded, or removed, as required. When both authors were satisfied that the coding was consistent and matched the coding manual, the extracts were analyzed to identify relevant findings. We report text extracts and labels in the following format: *"extract" THEME Participant ID*. Additionally, the links in the People, Processes, Technology (and Data) lens are denoted by underlining.

The coding manual and coded extracts are available at https://researchdata.aston.ac.uk/id/eprint/577/.

4. Findings

In recent years, the primacy of data as a driving force and prerequisite for IS driven change has emerged, principally through the concept of a data-driven culture in organizations (Fitzgerald & O'Kane, 1999). The importance of this perspective was revealed by our interviews, which reinforced the view that successful adoption of AI requires data to be first understood, available and managed. Participants reflected on the need to lay a foundation of data management, *"having to do the boring planning and how you structure your data, where you put it" DATA R2*, including technology which collects and stores data, since *"only if you have that data available could you possibly start saying, now how could I optimize my [process]" DATA R4*. They observed that data skills need to be acquired by people to achieve this *"the people who actually have to interact with the data, through to those who kind of manage those processes. So, in the past we've tried to bring those people along and educate them as to the reasons that we are trying to recommend these more open data approaches" PEOPLE D3.*

The importance of governance processes designed to curate data was raised: *"there has to be a lot of controls in place before [...] you can even get the data"* DATA D1. It was observed that people need to be educated about data requirements, because *"people's perception of what their data quality is doesn't always line up" DATA D3*. In terms of understanding, it is the people who operate existing processes who have to decide the relevance of data to the problem in hand *"we go through a process of defining what datasets and profiles will be required to deliver the solution" DATA B2.*

Data also determines the outputs of technology, and may drive the direction of AI developments. As one respondent observed, *"towards the end of the project they purchased some equipment [...] because that equipment allowed them to capture data better" TECHNOLOGY R3*. In a complementary manner, there is the need for data maintenance built into processes to ensure continuing availability of correctly configured data: *"they explicitly enable our app to have access to their product catalog to give them the working features, capabilities that they need." PROCESS/b B2.*

To reflect the reality of the importance of data we extended the triangle model, conceiving it as a tetrahedron with data at the apex, and links to and from the other elements as demonstrated by the above examples (see Fig. 2).

Finding: Data is an essential element of the socio-technical systems lens when considering AI.

Sections 4.1 to 4.3 report findings according to the stages of the innovation journey and draw out aspects related to the PPTD model. The stages were aligned to the TRL benchmarks identified by participants.

4.1. Laying the foundations of AI

The experts identified TRL 2–4 with work they carried out in a laboratory setting (TRL 1 projects were outside our study's scope). For example, a university working with industry partners for knowledge transfer or, in the case of consultants, as feasibility studies for clients. This level was valued as a space to think deeply about which processes are worth developing solutions for: *"Look at what a process looks like today, brainstorm how you might improve that current process" TRL-2 D1, "I think that stuff about creating a prototype and proving the value is a lot of the stuff that I do" TRL-4 D1.*

From this earliest stage, the influence of user-centered design on project teams was strong. Interviewees spoke of the need to involve stakeholders at different levels, in order to understand problems: *"we always try to bring in the end users right from the start, understand their day to day, understand their key pain points, and try to work out how we integrate emerging technology or AI into that to try to solve those problems" PEOPLE D3.*

Finding: The people who are stakeholders in the business processes can identify which AI applications will produce benefit.

Much of the development focus for AI projects was identified as similar to other data-driven MIS projects: putting excellent data management in place, identifying a process with business value and then matching technology to process. But at lower TRL levels in AI projects participants also spoke about identifying computational models which gave usable outcomes on experimental data: *"The way that we do it is that we build the models, we do the innovation. We test out a variety of techniques and evaluate them. We then say this is what we think is the right model." PROCESS/d R1.*

Finding: In TRL levels 2–4, selection of AI technology is distinguished from other MIS projects by a focus on testing computational models using realistic data.

4.2. Adoption of AI

The mid-range of the TRL scale, from TRL 5 to 7, covers the transition from a research environment to deployment in operational contexts. This can be a difficult phase of the innovation journey: *"The hardest thing is getting it out of a research environment and deploying it in an operational setting" TRL-6 B4*. Some technology transfer projects are strategically positioned at this point: *"We take for granted that you have these components, these enablers, already at a TRL level of 5 or 6" TRL-6 R4*. User involvement continues, including reflection on the impacts of new AI systems: *"on the client side, can see the product, can see the value and they're getting excited about something that's good to implement and there might be a bit of change management" TRL-6 D1.*

Any outstanding data governance issues must be resolved to work with operational data. Organizations with established expertize have an advantage: *"fortunately, we were working with some very smart [...] people in the first council and they had their own ethical process and a specific person that was managing that process" DATA B5*. However, for many organizations, a skills gap exists: *"there will be quite a while before people are just more used to handling data and understanding how they need to start collecting and storing data to utilize these more advanced techniques" DATA D1.*

By this stage, the development participants reported that they need to be clear about how successful performance is to be demonstrated. This

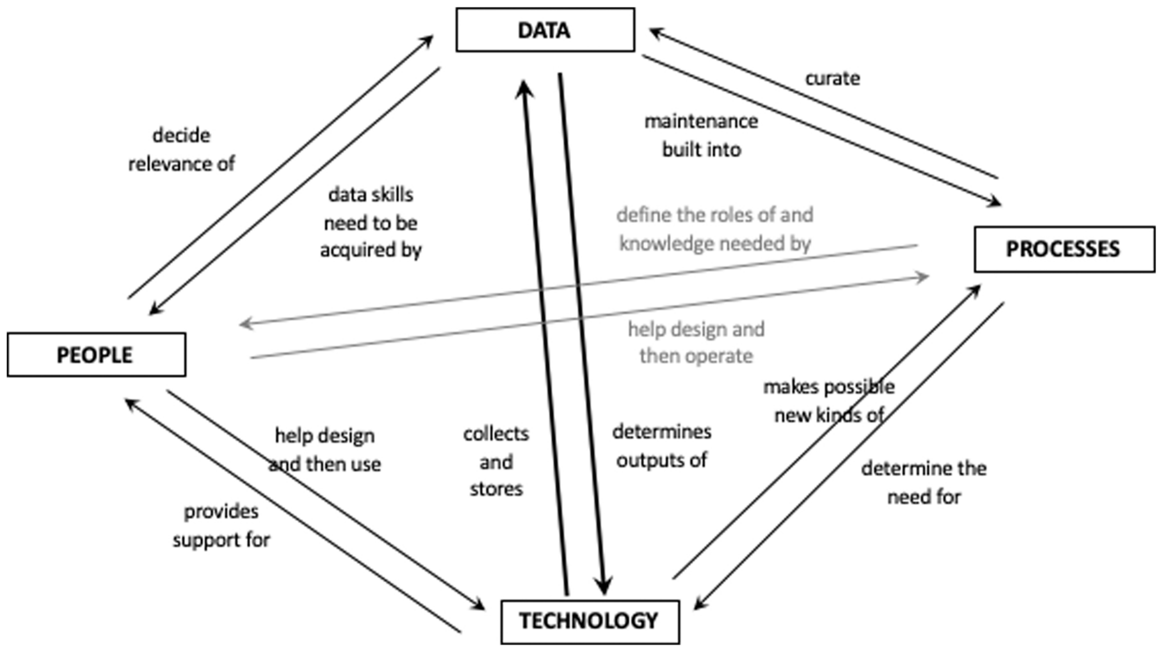


Fig. 2. People, Processes, Technology and Data (PPTD) extends Edwards (2005).

requires access to domain expertize within the organization, for example to provide gold standard training and validation datasets "*the current performance is as good as the radiographer in terms of the number of false positives and false negatives. But you had to have somebody who was a very good radiographer in the first place to train the AI.*" *PEOPLE B1*. However, some domain experts may be hard to access: "*the biggest problem they have is even if they are interested in adoption of AI technology in cardiology, for example, it's difficult for them to get backfill inside their organizations to free up their own time*" *PEOPLE B4*.

Finding: In TRL levels 5–7, collaboration between the development team and business functions is needed to bridge the gap to demonstration in realistic conditions. Specifically access to operational data and expert quality judgments are needed.

4.3. Mature AI

The experts reported that most organizations are not currently adopting AI at the higher end of the TRL scale. The large IT consultancies judged that for most clients they were still producing *"high fidelity, implemented prototype [application]s" TRL-7 D3*. One consultant (*D2*) put a figure of 10 % on the proportion of AI projects that go through to development of an operational system, indicating a possible valley of death issue for AI projects. At level 9, the need to integrate the AI system with the organization's MIS was noted: *"once it's proven and we learn from that, then we then say how do we productionize that and integrate it into production systems" TRL-9 D1*. This assures the live flow of data generated by processes into the technology, and thus makes the system fully operational.

Some technologies were reported to be easier to deploy than others, for example *"off the shelf AI" TRL-9 D1* like chatbots. One participant clarified this by comparing their work on semantic web technology to machine learning projects: *"those projects where the focus was on integration and management of internal data rather than on analysis, machine learning [...] some of them reached [...] TRL level nine" TRL-9 D4*. We infer that where the technology is at a higher TRL level the organizational readiness can be less. The entrepreneurs, who were all tech innovators, identified that some of their systems were in a more experimental state than others *"Our version 1 is out there and it's in use. Version 2 would be an evolution TRL 6" V1:TRL-9, V2:TRL-6 B2*, and *"ours are in the bracket between 7 and 9, mostly 9" TRL-9 B6*. This implies that organizations that are using AI that is at a lower TRL level need greater levels of organizational readiness to innovate.

The people implications of this include a need to build bridges between developers and stakeholders: *"People who know about the real world and how the real world operates don't really know very much about technology, OK. People who know about technology, who are typically in their late teens or twenties, may have done a technical degree, don't really know very much about the way the real world operates, right?" PEOPLE R4*. The IT consultants were accustomed to constructing teams that would bridge these gaps *"we've brought in domain experts from the client, so no technical experts but they completely understand the problem, and then we've supplemented that with our kind of user experience researchers and our technologists. And now we're starting to bring in technologists from the client side as well so we can transfer the knowledge as we're progressing" PEOPLE D3*. Participants observed organizations supplementing their teams with more technical expertize *"In case of really ambitious projects [...] organizations usually tried to also bring in, well, people with appropriate skills into their internal workforce" PEOPLE D4*. Sometimes these were hires from within the research team: *"[if] we have an MSc student doing a project, and it goes well. They like the person and they'll then hire them" PEOPLE R1*. For the entrepreneurs, the solution lay in building the skill set of their teams: *"we were very I think fortunate, and careful, that the first few people that we hired on the data science end had solid background in deployment" PEOPLE B6*.

Finding: Deployment of AI at TRL 9 requires integrating AI technology with data generated by processes, and developing technical skills and mutual understanding between the technical and business spheres of the organization.

When the findings (above) on the AI adoption journey are visualized in relation to the TRL (Fig. 3) it becomes apparent that data is important at every stage of the journey. However, the other elements to which data is most closely coupled change. At the foundation laying stage, it is the need to match the technology to the kinds of data available to address the business problem that stands out (model testing and selection). During the adoption phase the link to people is emphasized, as the data which captures expert judgment of the quality of AI outputs is needed to prove technology's value. Once technology is mature, the link between data and processes must be built into the organization's MIS infrastructure to maintain the supply of operational data. These observations further justify the addition of data to the socio-technical lens in the case

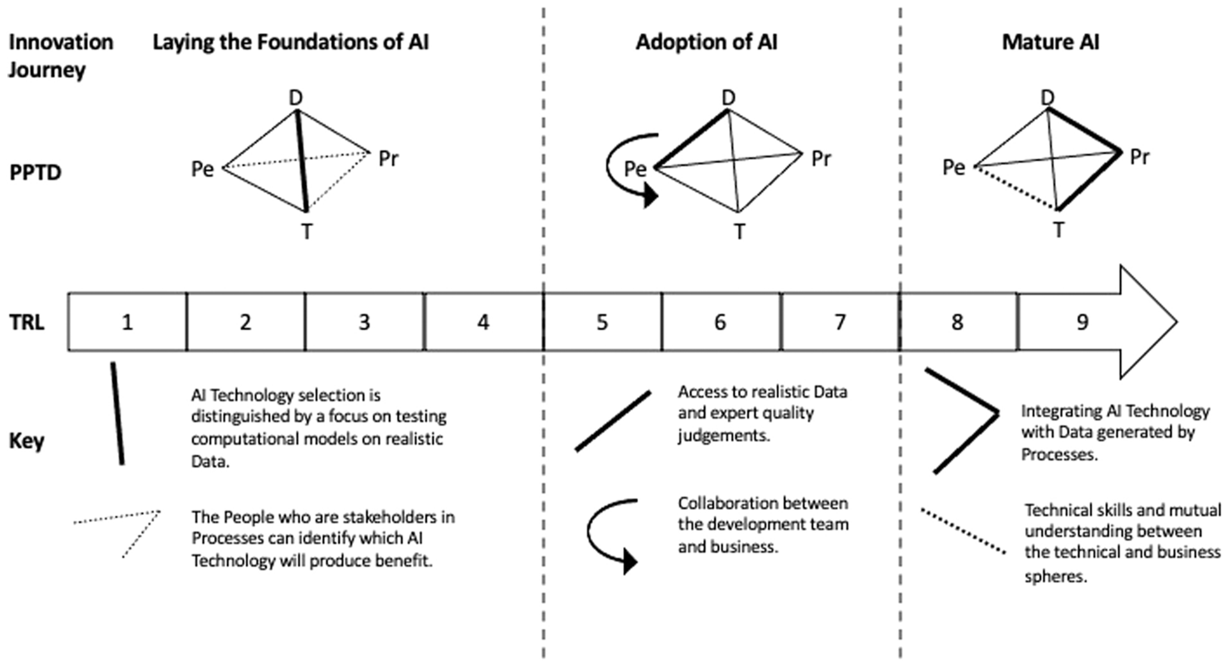


Fig. 3. PPTD innovation journey: elements of tetrahedron model aligned with the innovation stages and TRL.

of AI.

4.4. Impacts of AI technologies on processes and people

Thus far, we have looked at how the environment affects the development of the AI system, but now we start to look at how the system may affect the environment. This analysis draws together evidence about the destination of the AI adoption journey. Once deployed, mature AI systems change the ways that processes operate in organizations. A range of business processes were discussed, from sectors including health service provision, eCommerce, buildings management, and autonomous vehicles. Two modes of adopting AI into business processes were identified: optimization and disruption. Optimization delivers benefit by improving the efficiency and effectiveness of existing processes: "*can we cut costs, can we reconfigure our supply chain, can we do predictive maintenance. It's very much that optimization mind set." PROCESS/b D2.* By contrast, the disruption mode invents new processes which radically alter the business model: *"new models of software and business using these techniques to disrupt the market." PROCESS/b D2,* for example, *"could they then make smart predictions about [customers' needs] so they can do pre-emptive delivery or collection" PROCESS/b R2.*

Projects with an optimizing objective were often associated with organizations with established business models. Here the optimizing agenda is easier to sell to internal stakeholders than disruption: *"a lot of work to be done in how to roll out technology such as AI in a way that is less of a huge change for the kind of day to day process" PROCESS/b&d D3*. People in the organization may need reassurance that the AI is not a threat: *"if we can get the exec sponsor to say no jobs are going to be lost by this, it's basically to help us to support growth, that really helps the job security" PEOPLE* D1.

Disruptive changes can have societal implications, e.g., for safety: *"if it's an AI coffee machine, or something like that, we probably don't need to go very hard over on the safety argument for it, but if this is now going to be a heavy vehicle that's moving […] we're going to have to satisfy the legal requirement for a new set of safety arguments." PROCESS/b B1*. This can require sector level collaboration, including regulatory bodies, to determine which risks are acceptable and how they need to be mitigated and controlled: *"all the chief executives, all the regulatory bodies, the first time I think in years they've all sat together in the same room," PEOPLE B4.*

Finding: While AI systems with the objective of optimizing existing processes can be developed within organizations, disruptive systems produce societal change and require higher level oversight.

There was evidence in the interviews that deploying AI technology was drawing some business/operational processes closer to development. Establishing or modifying processes to generate the right kinds of data to feed into AI models brings the two functions together: *"Are you prepared to create a workflow, an interface, a platform, where people can, you know go through a series of steps, ask for specific services, and in the process, also capture that data so you can subsequently improve." PROCESS/b&d R4.*

Where there is good understanding of the business value of data, development and business needs converge on the same goals. One entrepreneur observed that the health wearables deployed in his patient group collected data which could be processed to meet the patients' (and care sector clients') objectives: *"these flags and indicators highlight well before hospitalization is necessary. Because what we're trying to do is manage you in the community and mitigate the cost." PROCESS/b&d B5.*

AI systems which evolve extend aspects of the development process into the business process because evolution may lead to a model developing biases. Evolution therefore brings with it a challenge for validation. To assure the quality of a model that keeps changing, testing and assurance processes from development will need to become embedded in the business process. In turn, issues in the real-world feedback into how the model should be built: *"They [robot cleaners] are learning an unintended reward scheme to improve their reward score and people are thinking, well do we want a reward scheme then?" SUCCESS CRITERIA B1.*

Finding: Organizational units that use AI need the resources to operate in a space which is closer to development.

There was an example of job enrichment, where a deployed buildings management system was augmenting building managers' roles and enhancing their status. Its aims are to "*make a prediction of […] the power consumption profile of that building*" *TECHNOLOGY B6* and to identify from sensor data *"anomalies that the energy manager should go and worry [about]" PEOPLE B6*. The interviewee emphasized that the buildings managers are *"a really crucial part of our business because they hold the knowledge that the AI will never have" PEOPLE B6*, but also that *"it moves* *that individual out of being overheads into being able to talk about the core business" PEOPLE B6*. Working with the AI had literally taken building managers out of a room in the basement and into strategic management meetings, because the AI enabled them talk about how to make changes to heating and ventilation systems which fed directly into reduced costs and improved margins. The building managers had been enabled by AI to become value creators.

Finding: One possible effect of AI on human job roles is job enrichment.

5. Discussion

5.1. Theoretical contributions and implications

Our findings concerning the People, Processes, Technology model have demonstrated the continued theoretical relevance of this perspective. Our findings, supported by literature on the role of data (Akkiraju et al., 2020; Alsheibani et al., 2020; Duan et al., 2019; Saari et al., 2019; Tarafdar et al., 2019) and data governance for AI (Cath, 2018; EU, 2021), lead us to propose an extension of the model to include Data. This model, which extends the PPT model to a tetrahedron with Data (D) at its apex (Fig. 2, PPTD model) and aligns it with TRL (Fig. 3, PPTD Innovation Journey) addresses the lack of an explanatory model which brings all four factors together and clearly delineates how the links between them are needed to build an environment in which AI systems can be successfully adopted. It addresses aspects of the lack of an integrated conceptual framework for AI decision-making identified by Dwivedi et al. (2021).

It could be argued that Data is implicitly subsumed by Technology within the PPT model, but we argue there are good reasons to separate them. The empirical evidence for Data as a separate factor in AI adoption presented here is supported by the inclusion of Data as a separate factor in recent AIMM and AI capability studies (Alsheibani, Cheung, & Messom, 2019b; Saari et al., 2019; Jöhnk et al., 2021; Mikalef & Gupta, 2021, Pumplun et al., 2021). These models reflect the data-driven culture in organizations (Fitzgerald & O'Kane, 1999) and the specific way that Big Data has fed the latest wave of AI (Duan et al., 2019). Furthermore, some aspects of data use are clearly social not technological. Ethics and data privacy, for example, are primarily social issues which require organizations to establish data governance to guide technological solutions. Lastly, and importantly, the extended PPT lens also highlights the critical relationship between Data and the business Processes that generate and consume it, a relationship which is critical to Data quality.

In the tetrahedron, technology is adopted and <u>makes possible new kinds of</u> processes, which <u>define the roles of and knowledge needed by</u> people, who help <u>design and then use</u> the technology, all the while driven by improving the links to and from data. Furthermore, by aligning the tetrahedron with TRL the extended model provides explanation of when and how the roles of the different factors change during the adoption journey. In particular, it proposes a changing emphasis on the relationships between data and the other factors as the adoption process proceeds.

5.2. Implications for practice

The extended model leads us to propose that, while technology readiness is an essential precondition, in order to innovate successfully with AI, organizations need to develop different kinds of readiness as the adoption process proceeds. The links in the model help provide explanations of when and why each kind of readiness is important. At TRL levels preceding operational system development (2–7) data readiness emerged as important. This is familiar from analysis of big data adoption e.g. (Jagadish et al., 2014; Klievink, Romijn, Cunningham, & de Bruijn, 2017). The need to systematically test the performance of machine learning algorithms to establish an experimental proof of concept may be less familiar beyond ML research environments. Papers about AI and business tend to mention model testing only in passing (e.g., Sjödin et al., 2021). Building people readiness throughout pre-operational TRL levels (2–7) emerged as vital to reach levels 8 and 9, as predicted by socio-technical literature, e.g. (Klumpp, 2018; Schidzig & Weinstein, 2017; Sutton, Arnold, & Holt, 2018). An important strategy involved putting together diverse teams in order to build mutual understanding between development and business functions, with parallels to the model proposed by Guillaume et al. (2014). At the operational TRL levels (8 and 9) establishing mature AI development processes, such as those outlined by Akkiraju et al. (2020), will be required for repeatable success. This provides an example of process readiness for development processes. However, business process changes are also needed for sustained operational use in order to embed tasks such as the collection and curation of data. This aspect of process readiness shows a notable lack of empirical research, though Makarius et al. (2020) discuss many of the issues.

We found that people readiness has more facets than just the well-known requirements for improved technical skills, technical support, and top management support. The need to involve stakeholders may come out of sound user-centered design principles, but it is reinforced in the case of AI by user fears of the impacts of automation and technology acceptance/resistance. Thus, organizations addressing stakeholder involvement and up-skilling should create a space in which business and technology functions are drawn closer together. This encompasses the need for business functions to understand how the data they produce feeds into AI systems and how evolving ML systems may modify outcomes. Evolving systems may, for example, need to deal with concept drift (Tsymbal, 2004) requiring their users to be capable of monitoring the technology's performance over time. This requires ongoing cooperation between developers and stakeholders, and upskilling of system users not just in technical skills, but also how to make decisions informed by AI outputs.

Building skills may mitigate employment fears. Willcocks (2020) predicts that automation will create some jobs: these findings suggest that some of these new jobs will exist in a space closer to development that requires users with technical skills. Our finding on the effect of AI on job roles is that the division in the literature (Wilson & Daugherty, 2018) between systems to replace people and systems to augment their performance is too simplistic. More subtle changes are possible, as with the job enrichment example. Furthermore, technically skilled users can develop the capability to use AI positively within organizations, avoiding oppressive scenarios (Kane et al., 2021).

The distinction between optimization and disruption mirrors that found in the innovation literature between incremental and radical change (Sumo, van der Valk, Bode, & van Weele, 2016) and that in the knowledge management literature between knowledge exploitation and knowledge exploration (Brown & Duguid, 2001). However, only the literature that concentrates on technology and social change attempts to address the wider issues resulting from radical innovation. The business and information systems literatures where the unit of analysis is the organization or the project rarely even mention them, with the notable exception of Stahl et al. (2021), whose entire focus is AI ethics and governance.

From a practitioner perspective, the difficulties identified with getting AI projects beyond TRL 7 are an example of the valley of death phenomenon. Practitioners who are aware of this can make strategic choices about whether to invest only in AI technologies which have high technology readiness (such as chatbots) or to accept that they are commercializing scientific research with the attendant risk/benefit trade-offs and must develop the capability needed to accomplish that. In order to reach the intended destination of the AI adoption journey, bridges need to be built between developers and business, to develop mutual understanding and the data and technology skills needed to sustain operational use of AI systems. Creating these bridges requires top management support not only for individual projects but also for developing social capital and creating conditions for knowledge sharing throughout the organization.

5.3. Limitations and future research direction

The study focused on projects that applied AI technology. The tetrahedron lens may be applicable to other technologies, for example analytics systems, that are being adopted by organizations with data-driven cultures. However, further work would be needed to generalize the model beyond the context of the study.

Our observations reinforce the importance of on-going research into the societal impacts of AI systems including themes such as ethical and responsible AI, e.g. (Floridi et al., 2018; Mittelstadt, 2019; Stahl et al., 2021). For example, In the UK, organizations like the Ada Lovelace Institute, The Alan Turing Institute and the Oxford Internet Institute are studying ethics as a core theme. Information management researchers have valuable expertize to contribute to this discourse which has impact on proposed legislation (EU, 2021; UK Government, 2021; Wired, 2021).

The people readiness actions we identified contribute to building social capital and knowledge, which both have positive effects on innovation (Pérez-Luño, Medina, Lavado, & Rodríguez, 2011). Current work on social capital and AI innovation is limited but suggests that the connection holds (Inaba & Togawa, 2021; Kuzior & Sobotka, 2019). Further work is needed on this aspect.

6. Conclusion

We have proposed a new model of the AI adoption process that combines technology readiness with a tetrahedron of socio-technical factors and emphasizes the central role of data and its changing relationship to other factors during the adoption process. The study provides findings concerning the need to attend to different kinds of readiness at different stages of the adoption process, and to build bridges between development team and business functions which may help to increase the number of AI projects whose journey advances organizations to, or at least towards, the intended destination of adoption.

Declarations of Interest

None.

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