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Abstract

Background: *Artificial Intelligence (AI) has become a ubiquitous phenomenon in recent times, with most organizations today attempting to maneuver their way around developing AI systems with the aim of improving the products and services they provide. However, what complicates developing AI systems is the paucity in frameworks to support organizations with AI System Development (SD). As a result, many organizations are using existing approaches which have been previously applied in earlier emerging Information Technology endeavors. This study explored how a framework can promote effective organizational AI SD. To achieve this a holistic framework for AI SD was conceptualized and examined from an organizational perspective.*

Method: *This study has examined the conceptualized framework People-Process-Data-Technology (2PDT) in AI, through a case study research design. The empirical data was analyzed based on 12 case studies within Australia including 39 interviews with AI experts. We have applied thematic analysis to investigate requirements of organizational AI SD.*

Results: *The results demonstrate that organizations are challenged by key factors, which inhibits their ability to effectively develop AI systems. For example, organizations are not achieving successful delivery of AI systems due to a lack of required skills. Additionally, a plethora of AI technology which is constantly evolving, poor data quality, and the paucity of AI SD frameworks are all contributing to unpredictable delivery outcomes.*

Conclusion: *This paper investigated requirements for effective organizational AI SD by examining the 2PDT framework. The results contribute to AI phenomenon by developing the requirements for AI SD, in terms of people, process, data and technology. It contributes to theory by evaluating and developing AI requirements for effective AI systems. The examination of the framework and case study approach added valuable knowledge to the AI domain. In addition, we contributed to practice by identifying requirements that organizations should consider in achieving better AI SD outcomes.*

Keywords: Artificial Intelligence, Case Study Research, People-Process-Data - Technology (2PDT) Framework.

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Introduction

Artificial Intelligence (AI) is an important Information Systems (IS) phenomenon. This is demonstrated by recent studies which focus on the importance of AI within the IS domain (Pai & Chandra, 2022; Tarhini et al., 2022; Win & Beydoun, 2020). IS researchers are motivated to examine AI related topics to better understand this phenomenon and to present findings which organizations can apply to create, process, and distribute data (Desouza et al., 2020; Mikalef et al., 2022; Pai & Chandra, 2022; Tarhini et al., 2022).

AI has captured interest of organizations worldwide. Organizations want AI in order to have machines complete tasks for people (Yigitcanlar et al., 2021; Zhang, Peng, et al., 2019) and to give them additional time to focus on more value-add tasks (Lee & Shin, 2020; Organisation for Economic Co-operation and Development, 2022). AI enables organizations to automate repetitive learning and discovery through data, add intelligence and self-learning capability to existing products, deeply analyze more data accurately and to get the most out of data. Organizations are using AI for business processes such as fraud detection (Zhang, Alvarez, et al., 2019), providing patient healthcare (Schiff et al., 2021), and policy development in government (Ras et al., 2022).

Research shows that AI is a significant technology of the fourth industrial revolution (Bawack et al., 2019). This revolution is predicted due to significant changes impacting areas such as systems and processes (Xu et al., 2018). Future of jobs report estimates that over time task-hours performed by machines will rise from 29% to 42% and that 54% of organizational employees would soon require a significant amount of reskilling (Watson et al., 2021; World Economic Forum, 2018). It is predicted that AI has the potential to add an extra estimated $15.7 trillion (+14%) to global GDP making it the most valuable opportunity for organizations. The retail, financial services, and healthcare sectors are predicted to benefit the most from AI (Rao & Verweij, 2017). Researchers have identified key challenges of AI for organizations. Examples include the difficulty with selecting the right algorithm for a use case (Baker et al., 2022; Dwivedi et al., 2021; Kelly et al., 2019), cyber security (Poulsen et al., 2020), and overseeing development of ethical AI systems (Choudhary et al., 2020). For example, Dwivedi et al. (2021) present detailed challenges of AI today which includes selecting the right algorithm. An important finding from the study is that the organizational focus nowadays is to exploit existing algorithms instead of developing new algorithms. This is resulting in complexities in finding the correct algorithm for an organizational use case. While exploiting existing algorithms can be a useful approach, it is also important for organizations to consider the right circumstances for building new algorithms to meet their specific requirements, and not rely on existing algorithms entirely. A further example presented by Poulsen et al. (2020) concerning AI systems, is with regard to cyber security. Whilst a cyber attack on organizational systems impacts confidentiality, integrity, and availability of systems and data. A cyber attack on AI systems such as a robot is greater as it can result in direct harm to people, where adversaries can exploit vulnerabilities to control robots to cause harm to people. Hence, there is a need for such AI systems to maintain a higher level of security through development of more effective security standards.

These are the aspects that have provided the motivation for this research which explored how a framework can promote effective AI System Development (SD). The aim of the study was to address the following research question – How can organizations effectively develop AI systems? To achieve this we have conceptualized a framework in the AI domain. We have employed a case study approach to analyze this framework and explore effective AI systems. Due to effective characteristics of the conceptualized framework, this research contributed to examining people and technology requirements, better process management, and effective management of data in the AI SD domain.

The 2PDT framework has been developed to bring structure and standardization within the AI domain. The 2PDT is justified as providing important theory serving as the framework for this study. Firstly, currently there are no frameworks within the AI domain which provide the means for a holistic end-to-end approach for effective organizational AI SD. Secondly, although AI is a key area of focus for organizations worldwide (Alnefaie et al., 2021; Organisation for Economic Co-operation and Development, 2022), only 15% of AI system use cases are expected to be successfully delivered (Sicular et al., 2020). Organizations have attempted to implement AI but have failed due to poor understanding of what AI is (Bawack et al., 2019). The 2PDT framework will enable organizations to examine the key requirements for developing effective AI systems, which will enhance their understanding of what AI is and ensure development of effective AI systems. Lastly, there are limited studies examining existing practices and methods which are employed in developing AI systems (i.e. requirements analysis, system design). This results in a lack of understanding and an evidence-based theoretical framework to identify possible deficiencies in existing practices and frameworks. The 2PDT enables organizations to assess their system development practices and methods, identify opportunities for enhancement, and implement required enhancements.

This paper presents findings from a study which examined the 2PDT framework which was previously conceptualized in Monshizada et al. (2021). Integrated into the framework are the key elements derived from the empirical findings which we recommend are useful for development of effective AI systems. The 2PDT framework will assist organizations with the end-to-end requirements of AI SD.

This paper proceeds as follows. Firstly the literature approach and key AI theory are presented. It then discusses how the 2PDT framework was conceptualized. It then discusses the research design for the study. Additionally an analysis and reflection on the empirical data is provided. We conclude with details regarding contributions of the study findings.

Approach to Literature Review

A review of relevant domain literature is a key requirement for academic projects (Badger et al., 2000; Webster & Watson, 2002; Xiao & Watson, 2019). This ensures a detailed understanding of the existing knowledge, assists with theory development, and to bring to light opportunities for additional research. We framed our systematic approach to review literature referring to key strategies and methods discussed by Webster and Watson (2002), Bandara et al. (2015), Badger et al. (2000), Okoli (2015), Kitchenham et al. (2009), and Xiao and Watson (2019). This included identifying search terms and selecting sources to assist with searching. Papers were selected following analysis of their title, abstract, and conclusion. The reference lists for papers were also scanned to identify any other relevant papers to analyze. We did not set a time span for papers, instead we focused on the content of papers as our criteria for inclusion and exclusion. Data extraction from papers included details such as what challenges does AI present for organizations, what are the application areas of AI, and what AI frameworks currently exist. Figure 1 illustrates this process used to search for and analyze relevant literature. Multiple data sources were used as there is no single database that contains an exclusive set of published papers (Kitchenham, 2004; Xiao & Watson, 2019). This included selected multiple databases, journals, and books.

The literature review was useful to study literature related to the study domain which led to identification of the research problem. The literature review findings also assisted to conceptualize the 2PDT using relevant IS theories and frameworks, and to finalize the research design. The empirical results were used to compare the themes found from the study to the themes found in the literature regarding key requirements for development of effective AI systems.

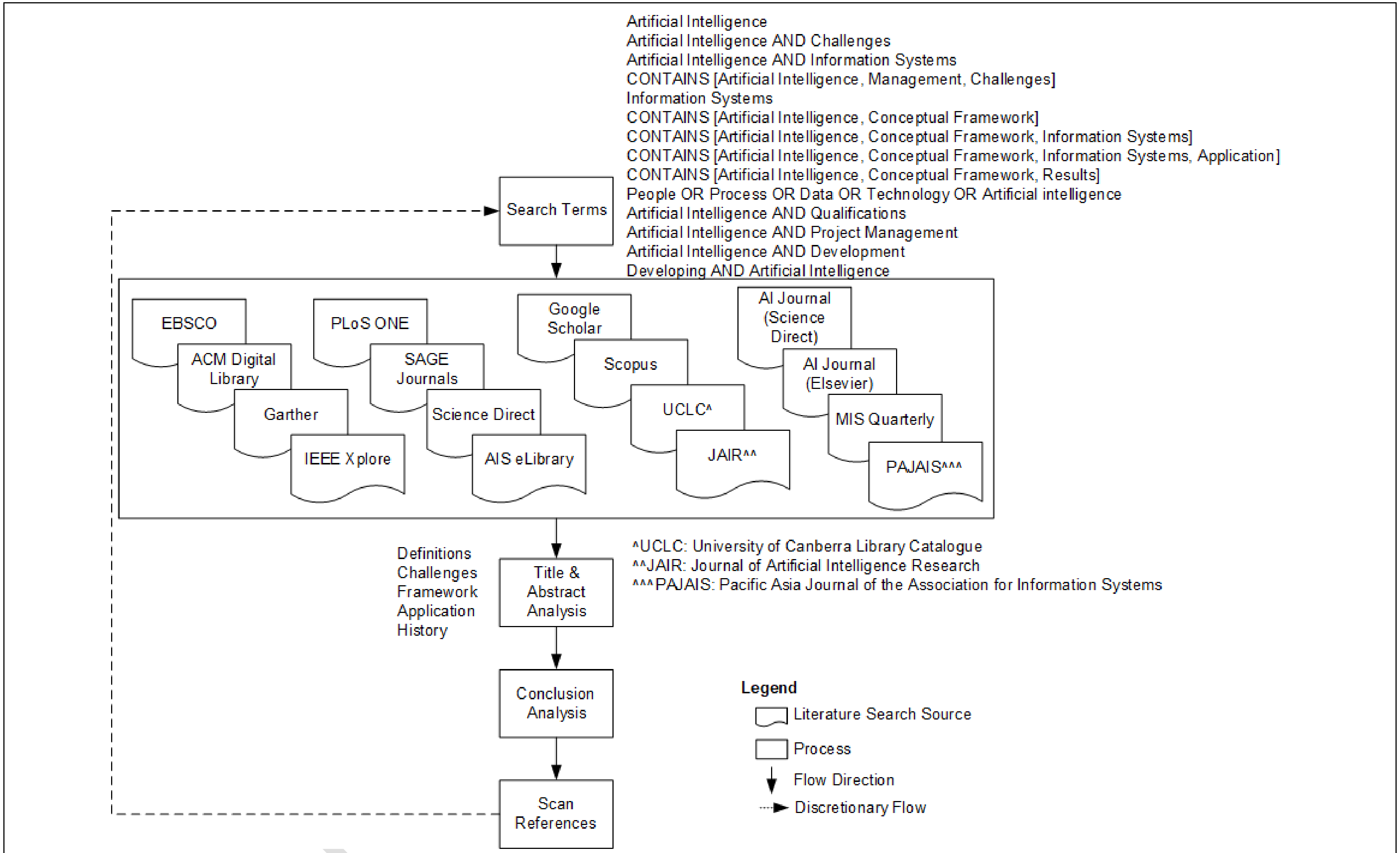

Figure 1 – Literature Review Process

The literature review assisted with identification of relevant existing literature using a variety of sources including databases (i.e. Scopus, Google Scholar), journals (i.e. Pacific Asia Journal of the Association for Information Systems, Science Direct Artificial Intelligence Journal), industry sources (i.e. Australian Government, Accenture), and books. The search terms included Artificial Intelligence, Artificial Intelligence AND Challenges, Artificial Intelligence AND Information Systems, CONTAINS [Artificial Intelligence, Management, Challenges], Information Systems, CONTAINS [Artificial Intelligence, Conceptual Framework], CONTAINS [Artificial Intelligence, Conceptual Framework, Information Systems], CONTAINS [Artificial Intelligence, Conceptual Framework, Information Systems, Application], CONTAINS [Artificial Intelligence, Conceptual Framework, Results], People OR Process OR Data OR Technology OR Artificial intelligence, Artificial Intelligence AND Qualifications, Artificial Intelligence AND Project Management, Artificial Intelligence AND Development, Developing AND Artificial Intelligence, System Development Lifecycle. The information analyzed assisted with creating a baseline version of the research question and preparing the research design.

AI Theory

AI has progressed over time from initially appearing in the world of fantasy (McCorduck et al., 1977), into becoming an important technological enabler within society today. This section provides background information about AI which aims to highlight how AI started and how it has progressed overtime. An overview of recent studies which are presented in the literature is provided to give an indication of the type of work that is currently of interest within the domain. The identified gap in research is presented including the existing related studies.

AI is defined in several forms, and this research has taken parts from a combination of definitions to present yet another definition. Having synthesized the available definitions we argue that our definition provides an appropriate description of AI. AI is a broad term that covers a collection of technologies and methods (Lacheca, 2018), and the science, engineering, and mathematics of building human intelligence and intelligent behaviors into an information system (McCarthy, 2007; Russell & Norvig, 2022; Xian, 2010).

The Turing Test (Turing, 1950) was the first academic experiment designed to examine a machine's ability to exhibit intelligent behavior. The idea of the Turing test was to assess if a computer can pass a test involving written questions. It would pass if the person interrogating the computer is unable to determine if the responses are from an actual person or from a computer.

McCulloch and Pitt (1943) are generally recognized to have first worked and written about AI (Russell & Norvig, 2022, p. 35). Their work proposed a model of artificial neurons that demonstrated a computable function could be implemented using connected neuron networks. Following this, the first neural network computer was developed by Marvin Minsky and Dean Edmonds at Harvard in 1950. Then comes what is known as the official birthplace of AI, in 1955 as part of the Dartmouth research project on AI (McCorduck et al., 1977). From the turn of the century organizations started to have large volumes of data at their disposal which shifted organizational focus to exploiting AI to get the most out of their data. Some examples of AI products today includes autonomous vehicles (Berente et al., 2021), and using AI algorithms to identify and manage email spam (Russell & Norvig, 2022, p. 47). Development and progress in both AI and its supporting technology has also enabled organizations to take advantage of AI. This includes improvements in computer technology specifically in the areas of processing and storage (Lee & Shin, 2020).

While interest and investment in AI has increased it is concerning that less than half of AI SD projects are expected to be managed successfully (Bawack et al., 2019; Sicular et al., 2020). One could argue that this bleak prediction is not dissimilar to the rate of successful management of the average Information Technology (IT) project. However, a study of existing literature highlights that organizations are facing several challenges that are unique to AI. This demonstrates that the failure rate of AI SD projects will be more significant. Examples of existing AI challenges includes, identifying appropriate use cases (Lacheca, 2018), obtaining people with the right skills to leverage AI (Ichishi & Elliot, 2019), and information security policies restricting use of AI (Alsheibani et al., 2019; Choudhary et al., 2020). A review of the domain literature also highlights the paucity of AI frameworks to support organizations with AI SD. Searching for AI conceptual frameworks (Cagan et al., 1997; Perez-Vega et al., 2021; Wirtz & Müller, 2019) found twelve relevant AI frameworks but they have a distinct focus regarding AI. There is little evidence of empirical results to demonstrate application of these frameworks.

Overview of Recent Studies

The study analyzed AI literature from 1950 to 2022. Some of the key themes and research studies AI literature has focused on include; application of AI techniques such as machine learning to find patterns in data and make predications (Ramos-Lima et al., 2020; Taheri et al., 2020; Wu et al., 2019), the use of explainable AI (XAI) to improve trust and transparency (Adadi & Berrada, 2018; Langer et al., 2021), and research about human thinking to better understand how much can be achieved with AI (Ahmad, 2017; Kowalski, 2011).

There are many recent studies which have examined AI in different contexts, and additional research opportunities are predicted to exist within the domain (Bawack et al., 2019). Examples of the scope of recent studies includes examining; the challenges and opportunities of delivering AI in government (Desouza, 2018), competencies needed to leverage AI effectively (Anton et al., 2020), management of AI (Berente et al., 2021), and factors which influence organizational adoption of AI in corporate social responsibility initiatives (Pai & Chandra, 2022).

There are also studies examining the challenges organizations are facing which negatively impact effective AI SD. Examples of challenges include a larger demand over the supply of AI skills (Ichishi & Elliot, 2019; Lee & Shin, 2020), determining risk versus value for AI investments (Adadi & Berrada, 2018; Sicular et al., 2020), and data lacking the required level of quality (Sun & Medaglia, 2019; Wirtz et al., 2019) to exploit AI. These challenges require a framework which can assist organizations to determine the key challenges within their environment and determine what actions can be taken to overcome them. It was papers such as these which provided the motivation for this study. Having seen the key challenges presented in the literature, we were committed to exploring how a framework can support organizations to identify and develop strategies to resolve the challenges preventing them from effectively developing AI systems. This led to conceptualization of the 2PDT framework which is discussed in the following main section.

AI studies have employed different research approaches for data collection and analysis including; mixed methods (Anton et al., 2020), pilot study and questionnaire (Pai & Chandra, 2022), multiple case study and thematic analysis (Sjödin et al., 2021). Recent AI studies demonstrate that diverse research approaches are being employed in the AI domain. However, AI studies employing a multiple case study approach appear to be limited, this is an area which this study will contribute to by employing a case study approach to examine a research problem. We have selected the case study approach to collect data as this approach will enable us to collect and analyze data which answers the research question. The domain literature and existing IS theory was also helpful in conceptualizing the 2PDT. The research design has provided essential insights which can assist other researchers. Researchers can determine how data was collected, analyzed, and what findings were produced. This can also assist researchers determine if the same approach would be the ideal approach for their research design.

Theories and Frameworks for AI

There are several studies examining AI frameworks (Kumar et al., 2020; Monshizada et al., 2021; Perez-Vega et al., 2021; Tsaih & Hsu, 2018) with the intention of brining standardization and structure within the domain. Such frameworks provide an opportunity for organizations to follow recommended approaches when developing AI systems. Application of these frameworks provides an opportunity for evaluation and evolution within the domain. The 2PDT is a useful framework for developing AI systems, which is justified by the applied research design.

The review of existing studies presented AI frameworks that have been examined in different domains like urban innovation (Yigitcanlar et al., 2021), a better society (Floridi et al., 2018), and public sector management of AI (Wirtz & Müller, 2019). We have summarized the existing theories and frameworks in Table 1 below. This table presents a framework description, their content relevancy based on the research problem, question and contribution. For example, the framework for ethical AI (Floridi et al., 2018) highlighted the AI domain from an ethical perspective while the study by Eschenbrenner et al. (2022) explored AI from a governance perspective, and a further study focuses on decision making in AI system design and development (Dobbe et al., 2021). While these studies have attempted to contribute to AI from different perspectives, they lack a holistic focus on the end-to-end requirements of AI SD.

The analysis presented in Table 1 illustrates that the common areas of focus in recent studies are people, data, and technology. It also highlights that there is limited focus on other areas such as ethics and business models. This research aims to examine a framework which is characterized by its agility, rigor, dynamicity, and completeness to contribute towards effective AI SD.

Table 1 – Categorizing Frameworks in Existing AI Literature

Paper	Framework Name	Framework Description	Autonomy	Beneficence	Business Model	Community	Data	Ethics	Explicability	Justice	Non-Maleficence	People	Policy	Project Management	Technology
Ashok et al. (2022)	Ontological Framework	Ethics framework for AI and digital technologies	x					x							
Auth et al. (2021)	Conceptual Framework for AI in PM	A conceptual framework for applying AI in the project management domain			x									x	x
Cagan et al. (1997)	Conceptual Framework for Combining AI and Optimization in Engineering Design	A conceptual framework for applying AI and optimization for improved computational design models													x
Chowdhury et al. (2023)	AI Capability Framework	AI capability framework in human resource management					x					x			
Dermody and Fritz (2019)	Conceptual Framework for Clinicians	A conceptual framework for clinicians who are working with AI and health- assistive smart homes					x					x			
Dobbe et al. (2021)	Hard Choices in AI (HCAI) Framework	A framework for hard choices in artificial intelligence system design and development						x				x			x

Table 1 – Categorizing Frameworks in Existing AI Literature

Paper	Framework Name	Framework Description	Autonomy	Beneficence	Business Model	Community	Data	Ethics	Explicability	Justice	Non-Maleficence	People	Policy	Project Management	Technology
Eschenbrenner et al. (2022)	Integrated Framework for AI Governance	A framework for AI governance comprising strategic, tactical, and operational elements.					x					x			x
Floridi et al. (2018)	AI4People	A framework for ethical AI technology design, development, and deployment	x	x					x	x	x				
Kumar et al. (2020)	Collaborative Framework for AI-IoT in Healthcare	A framework for using AI-internet of things (IoT) in COVID-19 pandemic situation for healthcare workers													x
Liu et al. (2023)	Efficient Framework for Banks	Data mining and AI framework for marketing in banks					x								
Méndez-Suárez et al. (2019)	AI Modelling Framework	An AI neural network modelling framework for forecasting copper prices					x								x
Perez-Vega et al. (2021)	Conceptual Framework	An AI framework for reshaping the contexts of online customer engagement behaviors										x			x

Table 1 – Categorizing Frameworks in Existing AI Literature

Paper	Framework Name	Framework Description	Autonomy	Beneficence	Business Model	Community	Data	Ethics	Explicability	Justice	Non-Maleficence	People	Policy	Project Management	Technology
Tsaih and Hsu (2018)	AI in Smart Tourism	A conceptual AI framework for better performance and impact in smart tourism					x								
Wirtz and Müller (2019)	Integrated AI Framework Model	An AI framework for integrating AI systems into the public sector			x								x		x
Yigitcanlar et al. (2021)	Conceptual Framework of Responsible Urban Innovation with Local Government AI	A framework providing guidelines to assist local governments in ensuring achievement of responsible innovation with AI				x							x		X

People-Process-Data-Technology (2PDT)

Conceptualizing 2PDT

A common research approach was used to conceptualizing the 2PDT which has been used in similar recent studies (Cagan et al., 1997; Dobbe et al., 2021; Kumar et al., 2020). This involved a review of the domain literature to identify the research scope, and to design the 2PDT. The literature review assisted to understand the existing knowledge regarding AI. This led to establishing that a high number of AI SD projects in organizations are failing due to key challenges within the domain (Berente et al., 2021; Sun & Medaglia, 2019). A framework was designed to assist with overcoming the challenges through effective AI SD. Relevant IS theory was analyzed (Hevner et al., 2004; Jessup & Valacich, 2008) which led to identifying IS concepts of people, process, data, and technology. Deep reflection of the literature findings and analysis of the above IS concepts resulted in constructing the 2PDT (Monshizada et al., 2021). The 2PDT provided the foundation for finalizing the research question, research design, data collection and analysis. The conceptualized 2PDT framework was examined using empirical data. This assisted to further examine the framework and to identify common themes for inclusion in the framework that can support organizations with effective AI SD.

Characteristics of 2PDT

The 2PDT (see Figure 2) is, a previously conceptualized, framework for AI SD in organizations (Monshizada et al., 2021). The 2PDT incorporates key components of interest within the IS domain to assist with capturing what issues organizations need to overcome in order to develop effective AI systems. This study adopted the components which were found to be of interest within the IS domain. This includes people (Jessup & Valacich, 2008; Lyytinen & Newman, 2008; Mehrizi et al., 2019), processes (Jessup & Valacich, 2008; Mehrizi et al., 2019), data (Jessup & Valacich, 2008; Mehrizi et al., 2019), and technology (Jessup & Valacich, 2008; Lyytinen & Newman, 2008; Mehrizi et al., 2019).

The 2PDT framework is not a system development lifecycle (SDLC) process. While the SDLC generally provides a process for planning, analysis, design, and implementation of an information system (Mantei & Teorey, 1989; Valacich et al., 2004; Zhang et al., 2005), the 2PDT will assist organizations with evaluating the environment for their AI systems regardless of the stage they are in (i.e. not started, in progress, implemented). This evaluation will assist in introducing or enhancing practices of AI SD. We however claim that the 2PDT complements the SDLC. Justified by its agility, rigor, dynamicity, and completeness; we assert that the 2PDT provides an effective framework that will support and improve AI SD. The agility comes from the expectation that the 2PDT can be easily integrated into existing organizational settings for developing AI systems. The rigor is provided by following an accepted research design which includes views of AI experts. Dynamicity is provided with continuous improvement being an important part of the framework to make it inherently adaptable to cope with change and progress made in AI SD practices. Finally, the completeness comes from bringing together a combination of existing theory and data collected from case studies.

The 2PDT shares common components and concepts with related frameworks. For example, this includes the key concepts of technology, data, and people. Process has not been identified as a standalone concept in these studies. Existence of these recent studies into AI frameworks demonstrates the need for more structure and standardization within the domain. While the study into development of the 2PDT is related to these studies, the 2PDT is a unique framework which can be applied for effective AI SD.

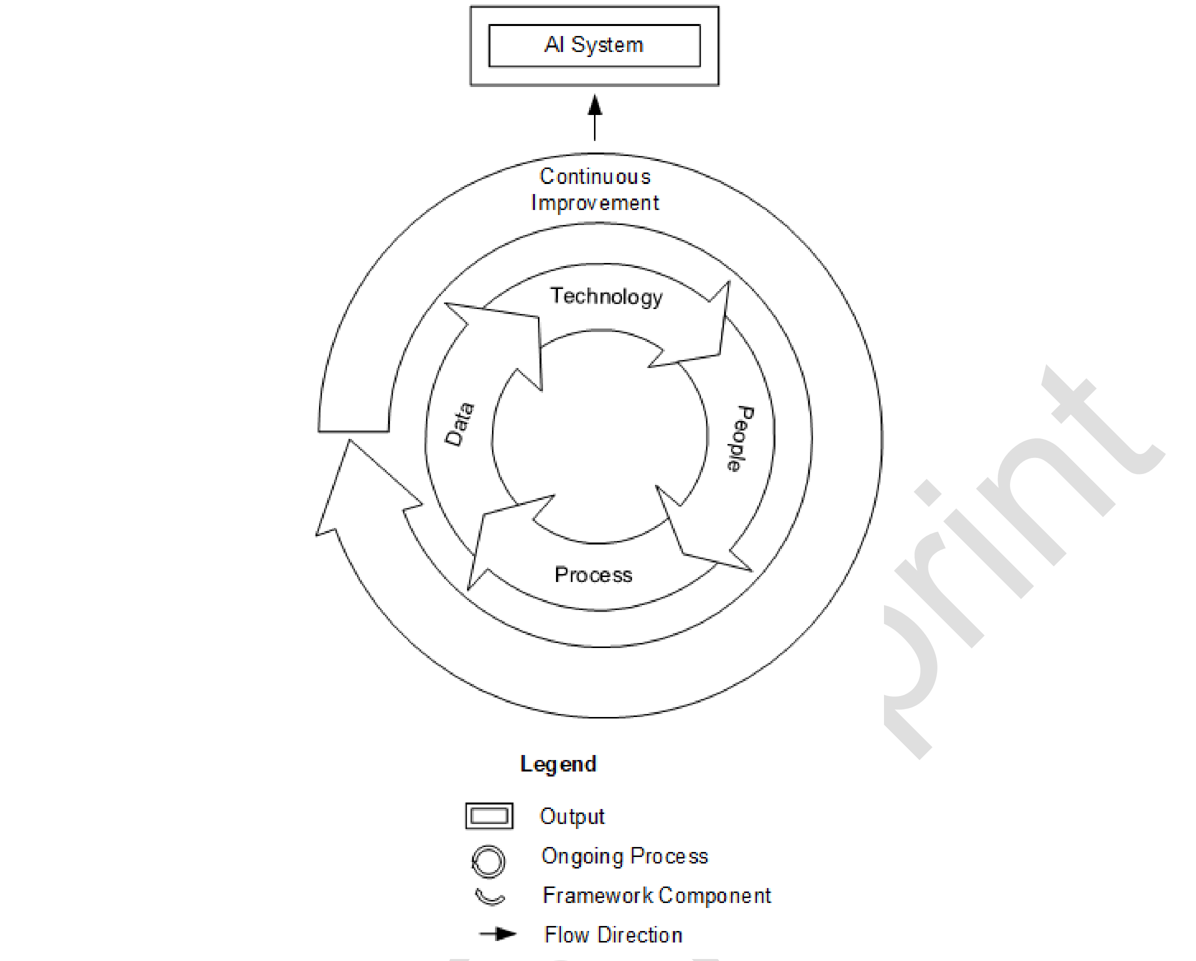

Figure 1 – 2PDT Framework

People

People are defined as those who build and/or use a system (Benyon, 2013; Jessup & Valacich, 2008) for example an end-user, developer, or an analyst. People play a key role in the development of AI systems as they develop appropriate use cases for AI SD and are involved in verifying AI output. AI is expected to always support human thinking and hence people will always be at the center of AI task performance and decision making (Deloitte, 2017; Xu et al., 2020; Zhang, Peng, et al., 2019).

Process

This involves the required activities that are performed to reach the desired goals when developing a computer system (Jessup & Valacich, 2008). For example, this can include the process of manufacturing goods, selling products, human resource management, and procurement. Examples of processes applicable to AI SD include processes such as ethics, use case development, system security certification, and algorithm selection.

Data

Raw substance which is recorded and can be in a formatted or unformatted composition (Jessup & Valacich, 2008). For example, an individual's date-of-birth or mobile number. Quality data is a key input for AI which means it must be structured and modelled effectively. Managing data quality (Desouza et al., 2020) in AI SD projects is an area which requires investigation to assess whether additional quality requirements exist.

Technology

A mechanical and electrical medium which consists of hardware and software that transform input data into output (Benyon, 2013; Jessup & Valacich, 2008). For example, a programming language or a computer system. Research indicates that AI technologies are well developed and relatively inexpensive today.

Continuous Improvement

The continuous improvement procedure is an important component of the framework, it is included to ensure ongoing refinement of requirements over time in relation to people, process, data, and technology. The purpose of this part is to encourage review and assessment as the framework is applied in practice. This step will identify the requirements that are accomplished and any new requirements which require additional focus.

Case Study Research Design

There are several leading approaches to case study research (Merriam & Grenier, 2018; Stake, 1995; Yin, 2018). This research followed the multiple case study approach presented by Yin (2018). This research employed a case study approach as it is commonly used in information systems research (Myers & Newman, 2007; Silverman, 1998; Trauth, 2000, p. 24). This approach assisted with understanding, exploring, and clarifying the nature of the research problem. Including multiple case studies has allowed better inferences to be made based on information gathered from more than one team and organization. All cases were randomly selected from twelve large organizations within Australia who had past or present experience in AI SD. Organizations had the opportunity to include one or more AI SD projects in the study. The research commenced after ethics committee clearance. The case study protocol has been included in Appendix A.

A pilot study was conducted to test the research design and formulated interview questions. This demonstrated that the case study approach was suitable for the study. The interview questions were well received by participants and the conversations flowed well from start to finish. A sample of the interview questions is provided in Table 2 below.

Table 2 – Sample Interview Questions
Sample Questions
Please outline the scope of your AI project(s) (please provide examples, case studies, any relevant documentation where possible).
Please outline the essential skills, experiences and/or qualifications required in your role and how can people acquire these?
Please describe the processes, framework and/or project methodologies you use to move towards achieving the goals of your AI project(s)? Where possible, please provide related documentation (i.e. project plan, process/framework details), and/or references (i.e. research, case studies).
Please outline the challenges which arise in delivering AI project goals?
How important is data in your AI project(s) and how do you manage data in the delivery or implementation of your AI project(s)?

The main study was conducted with additional cases and interviews to collect and analyze more data. Overall the case study approach has proven well suited for this study as it offered a flexible format for data collection. It has offered a distinct feel of the world that statistical analysis through quantitative research cannot provide (Boodhoo & Purmessur, 2009), it also offered flexibility with the collection, analysis, and interpretation of data and information (through semi-structured interviews, and document analysis).

Table 3 includes details of the cases including the number of people interviewed, and documents analyzed. Case 1 is responsible for ensuring Australians can experience the wellbeing and economic benefits that quality education, skills and employment provides. Case 2 is a multinational technology company producing hardware, software, and systems. Case 3 manages Australia's revenue collection, and administration of payments and services. Case 4 administers collection and analysis of national statistics to assist Australian federal and local governments. Case 5 is a government agency administrating welfare, health, and child support payments. Case 6 is an Australian research university that works with government, business and industry, and communities. Case 7 is a government department responsible for protecting Australia and its national interests, while also promoting international security. Case 8 is a government agency made up of directorates which are supported by a central information technology area. The organization is responsible for providing local government services. Case 9 is an Australian government agency responsible for law enforcement policy management and national security. Case 10 is an Australian government agency responsible for whole of government information and communications technology and digital policy, strategy, and leadership support. Case 11 is also an Australian research university who works with government, business and industry, and communities. Case 12 is an Australian government agency responsible for law enforcement. Interviews were conducted individually with two participants nominating an observer to be present during interviews. The findings were merged for discussion at the individual case level. With the exception of Case 10 and Case 12 all other cases included multiple interviews.

Table 3 – Case Details

Case No.	Sector	Organization Size (No. of Employees)	Number of Interviews	Number of Documents
Case 1	Public	Large (1001-10,000)	8	17
Case 2	Private	Extra Large (More than 10,000)	5	7
Case 3	Public	Extra Large (More than 10,000)	3	7
Case 4	Public	Large (1001-10,000)	3	10
Case 5	Public	Extra Large (More than 10,000)	3	5
Case 6	Academia (University)	Large (1001-10,000)	3	2
Case 7	Public	Extra Large (More than 10,000)	3	11
Case 8	Public	Extra Large (More than 10,000)	3	14
Case 9	Public	Extra Large (More than 10,000)	3	9
Case 10	Public	Medium (251-1000)	1	1
Case 11	Academia (University)	Large (1001-10,000)	3	3
Case 12	Public	Large (1001-10,000)	1	1
Total 12			**Total 39**	**Total 87**

The documents collected were either provided or referred to by participants during interviews, or were documents obtained by the interviewer from the participating organization website. The type of documents shared by participants included project management documentation, published AI papers, and technology related strategy documents. The type of documents obtained from organization websites included corporate plans, data plans and strategy, and security strategy. Interview participants included AI executive, senior managers, and practitioners. Examples include; Data Scientist, Chief Digital Officer, Chief Data Officer, First Assistant Secretary Analysis and Data.

Criteria to Judge the Quality of Research Design

To judge the quality of the research Yin's four tests were applied (Yin, 2018, pp. 42-46). The four tests include construct validity, internal validity, external validity, and reliability. These tests were conducted using eight tactics at separate phases during the empirical research. Figure 3 illustrates which tactics were applied at which phase of the research to safeguard quality.

Construct validity was managed by collecting data from multiple cases and documents, and this included providing draft write-up of interview transcripts to participants for review and validation. Internal validity involved application of thematic coding and analysis, and cross case analysis with the aid of NVivo data analysis software which is recommended for data analysis in case study research. External validity was ensured by including multiple case studies, and using saturation for determining the sample size for the study (Guest et al., 2020; Mason, 2010). Saturation in the study was determined after seven cases were studied. Reliability was managed using a case study protocol, using NVivo to develop a data warehouse, and using Yin's (Yin, 2018, pp. 134-135) process to maintain a chain of evidence.

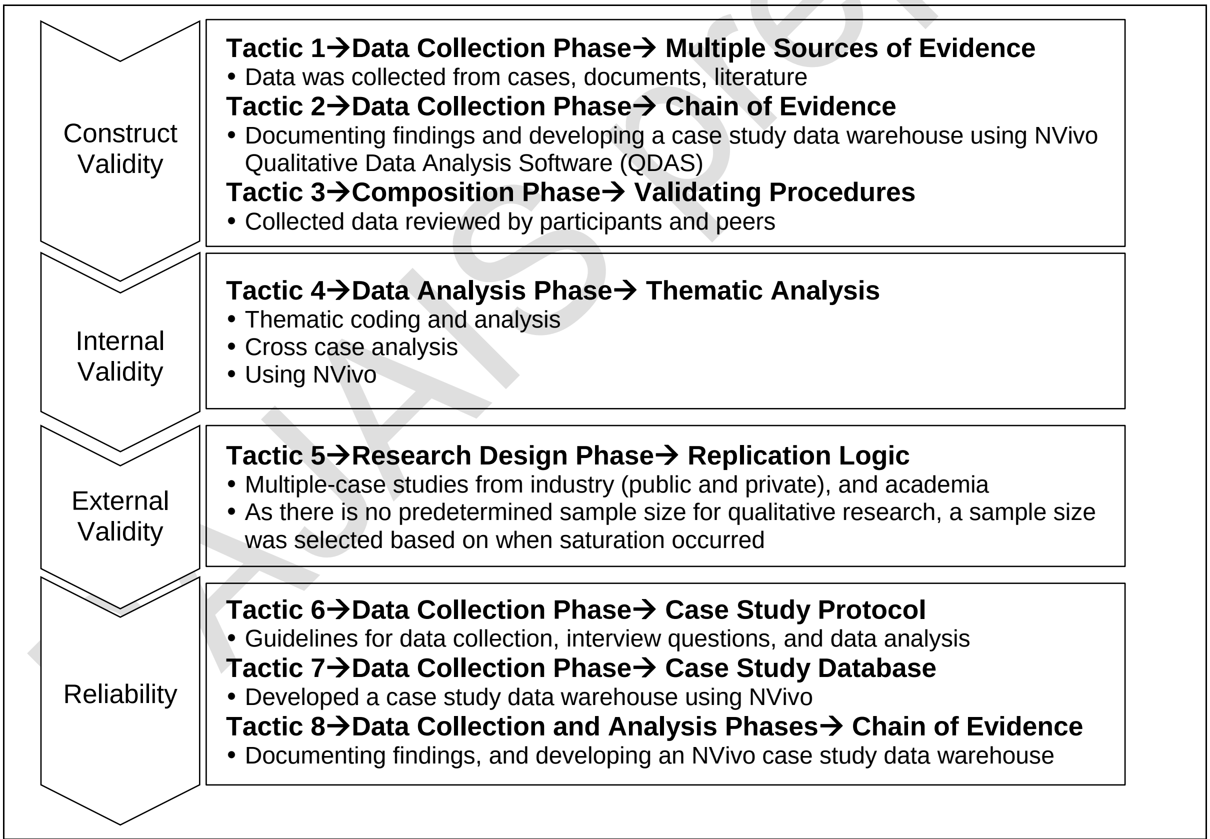

Figure 3 – Case Study Tactics for Four Design Tests

Thematic Analysis

The research followed the thematic analysis method to analyze and explain patterns in the research dataset (Braun & Clarke, 2022, p. 4). This included following the six phases of (1) dataset familiarization – examining the collected data to get familiar with it and to know what information has been gathered. (2) data coding – identifying data segments which are relevant to the research question. This involved using a combination of research questions, literature information, and the interview data. NVivo was used to assist with this, creating multi-level nodes to group codes. (3) initial theme generation involved identifying patterns across the research dataset to identify themes. Commonly used themes were selected to show how they could help organizations. (4) theme development and review – involved assessing initial themes and making any necessary revisions. (5) theme refining, defining, and naming – involved concluding analysis of data and finalizing themes in preparation for the writing phase. (6) writing up thesis and this journal paper.

How Themes Were Developed

Themes were developed using the data collected as part of the research and included data familiarization, theme generation, reviewing and refining themes. Figure 4 illustrates the process followed to develop themes from the research data.

Themes were initially developed using findings from the literature review. The purpose for developing themes using literature data was to assist with understanding the existing themes that could be developed in relation to the research question, and to assist with finalizing the interview and research questions. In the data collection phase of the research, interview and document data was obtained as part of a pilot and main data collection phases. The interview data included the answers provided by participants during the interview, and the interview documents included documents shared by participants and documents obtained by the researcher from the participating organizations websites. The collected data was used to review and refine the themes initially developed.

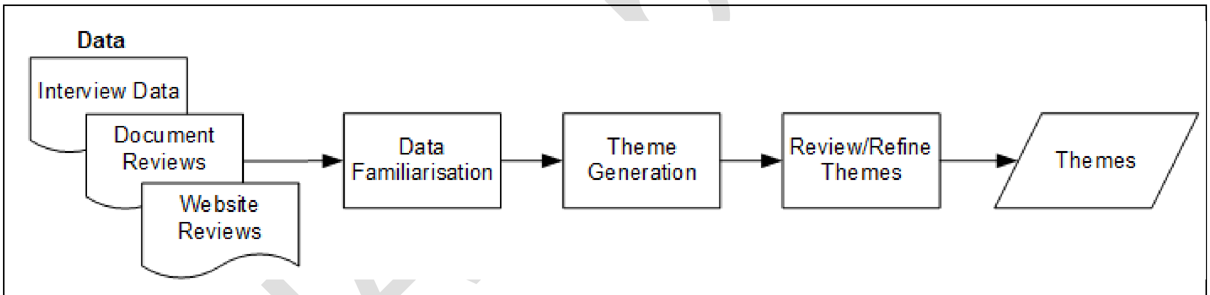

Figure 4 – Theme Development Process

Analysis of Empirical Data

Figure 5 presents the initial empirical version of the 2PDT framework for effective AI SD in organizations. We have firstly presented the framework including the requirements recommended for organizations to apply which have been established from analysis of the empirical data. This involved following the thematic analysis process described above. These requirements are presented in the boxes on the outside of the concepts of people, process, data and technology, and they are discussed below. This framework will support organizations with effective AI SD. Organizations should work through the identified requirements to ensure they have clear actions in place to implement them. Organizations can follow the requirements provided but should also identify and consider other requirements which are suitable for them as part of the continuous improvement cycle.

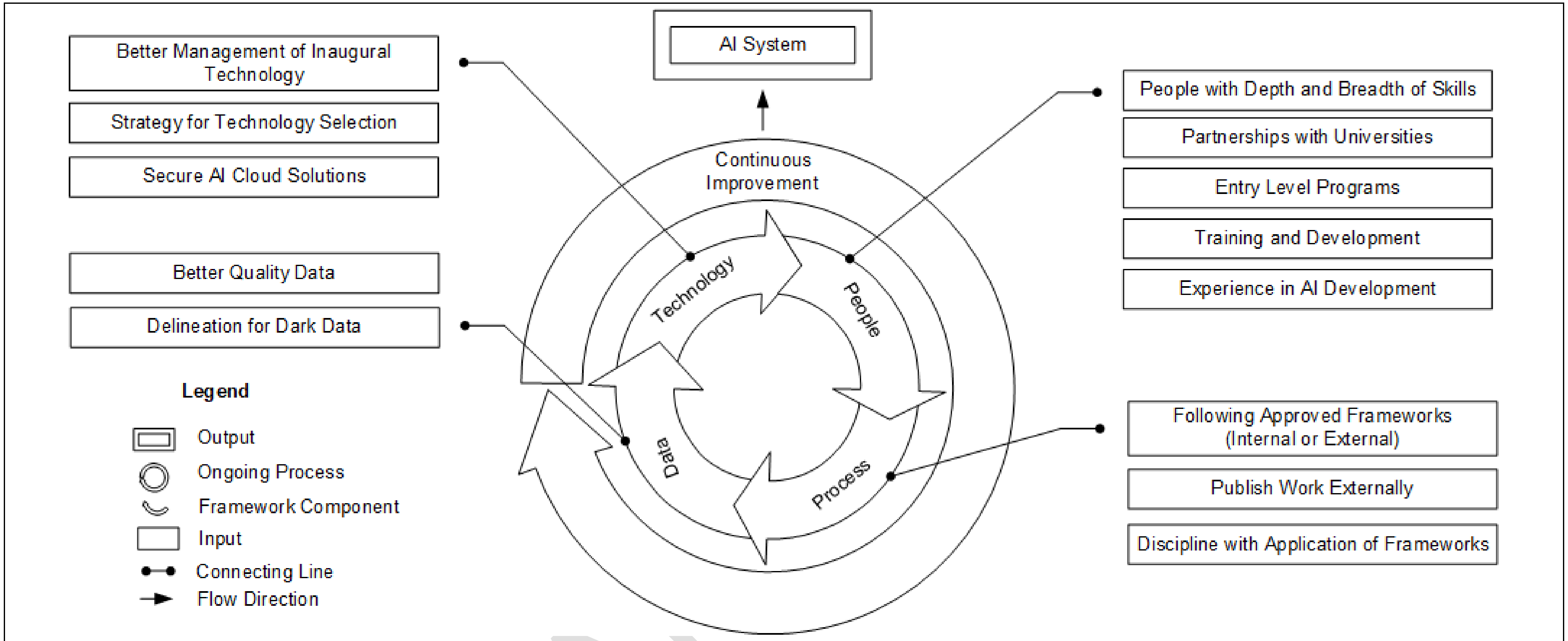

Figure 5 – 2PDT Framework with Empirical Inputs

We claim that the agility, rigor, dynamicity, and completeness of this framework brings visibility and provides structure to examine AI SD. The agility refers to the ability of easily and quickly integrating the framework into the existing organizational process of AI SD. The rigor comes from a study which follows an accepted research methodology which includes the views of AI experts. The completeness comes from a mix of existing theory which is brought together to construct the framework (Monshizada et al., 2021). The framework provides efficiency, efficacy, better performance and outcomes. It will also enable organizations to manage their people, improve processes and data, and better exploit AI.

The domain literature presents challenges which can negatively impact AI SD within organizations. Comparing these findings to our empirical data highlight's new themes which have been found in this study (see Table 4). A cross in the second column indicates that the given theme was not mentioned in the domain literature which was studied. A tick in both the second and third columns indicates that an emerged theme from the research was also discussed in the domain literature studied. These are important findings which will facilitate organizations to make changes to improve how they develop AI systems. After these changes are made organizations can also assess the results they produce.

Table 4 – Empirical vs Literature Findings

Themes	**In Literature**	**Empirical Data**
People		
High Demand for AI Skills	×	✓
Low Supply for AI Skills	×	✓
Lack of experience and skills to leverage AI	✓	✓
Attracting People with AI Skills	×	✓
Retaining People with AI Skills	×	✓
Process		
Paucity of AI Frameworks	×	✓
Vague Guidelines for Existing Frameworks	×	✓
Data		
Poor Data Quality	✓	✓
Dark Data	✓	✓
Technology		
AI Technology is Inaugural and constantly changing	×	✓
Plethora of AI technology	×	✓
Security Risks with Overseas Hosted AI Cloud Services	×	✓

People

Firstly, the demand for AI skills is high but the supply is particularly low at present making it extremely competitive for organizations to secure the skills they need. As a result organizations must work with what is available to them. *"There's not a lot of people who have those skills out in the field"* (Interview-3.1). This makes it challenging for organizations to find experienced AI professionals. While it is important to have people working on AI SD projects that have prior experience, this does not mean the entire team need to have prior AI working experience. Teams can comprise of a mix of people with prior AI development experience working and mentoring team members who can learn on the job and undertake additional training. Organizations who divert existing resources or engage resources who do not have AI SD project experience alone are experiencing challenges in progressing AI system projects to closure. *"The organization [has] the experience but not in delivering that type of technology and using the required toolset"* (Interview-1.8). This highlights that experience in working with AI technology and required toolsets are essential for successful delivery of AI SD projects.

Secondly, it is difficult for organizations to attract and retain AI practitioners, notably those organizations that are considered novices with regard to AI. Along with the extremely low supply of AI skills it highlights the need for organizations to invest in training and development for interested staff, including investment in entry level programs such as university graduate programs. It was highlighted that attracting and retaining AI practitioners is difficult:

> *"Around the globe at this moment, there's a skill shortage, right? There are two things. One is the skill shortage and the way the industry is evolving, it's so traumatic and so exponential growing. It's very hard to retain the employees. If you have got someone really good, it's really hard for us to retain those employees. Because they're going to be going to another organization in next two, three years' time".* (Interview-6.2)

Organizations are also taking advantage of university partnerships by investing in research projects and accessing the skills required to assist with AI SD. This includes engaging with universities to create Doctor of Philosophy (PhD) projects, and on boarding students into the organization to work on required AI SD projects.

Process

There appears to be a paucity of standards and frameworks for AI SD. Vagueness refers to standards being applied based on organizational preferences such as, what is perceived to be a good organizational fit or not. Some organizations have not identified the ideal frameworks and toolset for developing AI systems. *"We haven't had the kind of frameworks that they're looking for that they need to be able to do what they want to do, or how they want to do it, and so that means we lose them quickly"* (Interview-1.3). This is referring to AI practitioners. A better approach could be to engage practitioners who can assist organizations to standardize the frameworks and toolsets that are important for developing AI systems. There are limited number of formal frameworks for developing AI systems. *"Because there's nothing out there"* (Interview-3.2). As a result some organizations are developing this internally such as *"ethical and emphatic framework"* (Interview-2.1).

It is also important for organizations to publish progress of their AI work externally to help with getting feedback, and to make better progress in the domain through knowledge sharing and eliminating effort duplication.

Another interesting finding was that organizations do not strictly follow best practice frameworks. With regard to Agile project methodology it was found that it is relatively being employed:

> *"So we sort of have the idea, we do not do it at all, like properly, I guess, in terms of if you were an agile HR practitioner or something or certified agile HR practitioner, you'd probably be quite horrified. But I guess we adapt it for our particular situation".* (Interview-4.1)

Whilst such frameworks are flexible and adaptable, to meet organizational needs the essential elements need to be applied to ensure organizations realize the benefits expected from them. Owners of such frameworks could assist by providing information for organizations to establish the core elements of their frameworks which must be strictly followed in a more disciplined manner. For example, it was highlighted that having a disciplined approach is essential. *"We* *have to have established disciplines around a lot of stuff like documentation like consideration of data and governance and capture and all that sort of details"* (Interview-1.4).

Data

The empirical data highlights that organizations have particular robust data management practices in place. They are also setting themselves additional targets to continuously improve in this area, for example, developing standards for ethical use of data. Most organizations have an office of Chief Data Officer who is responsible for overseeing enterprise-wide governance and utilization of data assets. Organizations have data strategies in place that detail the approach that will be applied to use data ensuring organizational priorities are met. Within government there is a strong focus on data integration and currently multiple agencies are working in partnership on the Multi-Agency Data Integration Project (MADIP). This initiative is aimed at providing insights about the Australian population in relation to use of healthcare, education, and employment. A common trend is the use of data warehouses or data lakes that use point-in-time data, and there are plans to assess use of real-time data in the future. Data security stood out as a key area of focus for organizations. Organizations have structures in place to maintain a strong information security posture. These are in line with international standards such as the ISO/IEC 27001 and 27002, ISO 15408, and IEC 62443.

Challenges with Data

Data is a key requirement for developing AI systems (Anton et al., 2020). Two important data requirements to support development of effective AI systems are better quality data (Choudhary et al., 2020; Ichishi & Elliot, 2019) and improving management of dark data (Heidorn, 2008). Organizations must focus on these two requirements to overcome challenges such as erroneous results from AI systems and important data being underutilized in AI SD.

Better Quality Data

Data quality is about having accurate, valid, and complete data to use for developing AI systems (Desouza, 2021). Without the right data that meets quality requirements it is not possible to successfully exploit emerging technologies such as AI. A key finding of the study is that AI development teams are presented with poor quality data to work with. In general the cases referred to substandard levels of data quality existing in their environment which is a result of not having an enterprise approach to data production and management. This includes poor metadata and data lineage information, data in disparate systems and different formats (internally and externally), incomplete data, and data duplication. For example, it was found that data quality challenges are an alarming issue for organizations. *"One of our challenges, of course, is quality of data. That's a challenge everywhere I guess, healthcare is renowned for [being] challenging. We've got, at the moment, more than 220 systems that we're trying to integrate"* (Interview-8.1). This requires manual intervention which is time consuming, and organizations are looking into tools which may be able to make this more efficient in the future. Organizations are setting target levels of data hygiene that involve data cleansing, validation, and measurement (ensuring sufficient data is available). There is a shared view on centralizing data management to drive improvement of data quality.

Dark data

Another interesting finding is that organizations own a large amount of dark data. Dark data refers to data which is acquired by organizations in the course of providing services (Heidorn, 2008), but usually fail to exploit it for other purposes such as simple analytics to developing AI systems. Dark data is a concept that is understood but not proactively managed at this moment:

> "*We either have sparse data, we just don't have enough data to make the assessment, to build the model, or a proliferation of data or whatever you want to call it, dark data, data that we just don't know if it's any good for what we're trying to do*". (Interview-2.1)

Data modelling practices do not seem to identify dark data, and this creates an environment in which what is described as dark data being open to interpretation and subjectivity. Without appropriate management of dark data organizations are making it challenging for their people to effectively exploit data to leverage AI systems. Organizations should benefit from further research and development of guidelines to assist with management of dark data.

Technology

There are a wide range of technologies available in the market which organizations are using to develop AI systems. Although some robust systems can be built with them at times the potential of what can be built is over-hyped without a good understanding of key factors. The empirical data highlighted this where two participants said, *"I also think that there's a misconception that it's just some sort of magic"* (Interview-1.3), and *"they have uses, but I think, I wonder if they're over hyped at times"* (Interview-1.5).

AI Technology is Inaugural and Constantly Changing

AI technology can be described as being inaugural in nature and constantly changing. This means organizations are investing in technology that has not been comprehensively evaluated which may result in unexpected outcomes such as several tools that do the same thing. For example, in relation to this the following was discussed. *"We have every visualization tool under the sun, and we have every analytical tool under the sun. It means that you're training load is huge"* (Interview-1.5). Other unexpected outcomes incudes incompatibility issues with legacy systems or the vendor's lack of experience to support a client in the application of the technology for particular use cases. Some organizations accept that there are challenges which need to be worked through to ensure AI technology delivers desired outcomes. Likewise, they accept that they may learn a particular technology will not give them desirable results. Additionally, the inaugural nature of AI technologies along with organizations not having mature processes to use them currently both make it difficult to maximize the return on their AI investments. It appears that some vendors acknowledge that their technology is inaugural and are working diligently in partnership with customers to enhance technologies as opportunities are identified. Although it is unclear whether this is included in the marketing and sales discussions. Nevertheless, organizations are proactive to get the best out of AI technologies through educating their staff, developing roadmaps and patterns, encouraging a culture of experimentation and prototyping, and not being afraid of failure. To reduce the risks associated with investment in inaugural technology organizations must develop clear strategy to support technology selection and develop relevant clauses in vendor contracts.

Plethora of AI technology

Organizations are experiencing an ecosystem where there is also a plethora of AI technologies, and this makes it expensive for organizations to invest in several technologies:

> *"Then the AI stuff we're using, a lot of it mostly is off the shelf, right? We're talking about using existing frameworks, TensorFlow, this, that, whatever, right? You know Python has a number of libraries we tend to use. Cloud, Open Source, Amazon, Microsoft Tableau high performance computing*". (Interview-11.2)

Additionally it was explained that *"There's a lot of technology out there"* (Interview-7.3). A plethora of AI technology has a negative impact on government organizations in particular, as they have strict protocols and are unable to invest in multiple technologies that provide agnate potential with minor extras. In addition, they have other associated costs including additional training for staff or recruiting people with knowledge and skills with additional technology. This plethora also provides the temptation for practitioner experimentation. Identifying a standard toolset and having a process in place allowing practitioners to access and experiment with the latest tools will provide better outcomes. Organizations need to carefully select what AI technologies best meets their needs, and also be cognizant of the need to remain flexible to change AI technologies. For example, when the benefits of such a change are identified and it is obvious that it will enable them to achieve better results.

Security Risks with Overseas Hosted AI Cloud Services

A key technology that organizations have either already acquired or are in the process of acquiring is cloud technologies. Organizations are seeing benefits in cloud technologies namely cost savings, and the potential to easily access software without the need to procure and configure them in-house using on-premises infrastructure. With all the interest surrounding cloud technologies it is important to remember that not all cloud services are currently appropriate for organizations in Australia. For example, government organizations are unable to use some cloud AI services as they are only available in overseas data centers:

> *"I now need to think, is SageMaker operating in Australia or is it operating in the US, or is it operating in Shanghai or Mumbai? What's the challenge for SageMaker to be using my data? Is there data in there that's got data sovereignty issues?"* (Interview-8.2)

The security policy for federal government requires cloud providers to meet strict security requirements which includes government data not exiting the country. It is prudent for cloud providers to resolve this issue which would provide a good outcome, making it possible for organizations in Australia to take advantage of all cloud AI services.

Reflection on Empirical Data

This research examined AI from an IS perspective following an approved approach to conducting research. The research contributes to theory and practice which supports organizations with effectively developing AI systems within society. This will result in development of better services, policies, and programs. The 2PDT framework will bring more structure and offer a standard approach to developing AI systems which academics can advance further, and industry can apply and evaluate. Additionally, the 2PDT contributes to timely debate within the domain in relation to developing AI systems in society.

Case study research is new within the AI domain where more focus is on the science, engineering, and mathematics of AI. There is also a paucity of AI frameworks within the domain to assist organizations with developing AI. The 2PDT is presented to researchers and industry to apply, evaluate, and to encourage debate. We predict that the framework requires practical application as a next step, so it can be enhanced based on feedback and lessons learnt. This provides an opportunity for future research which can further guide and refine the 2PDT.

In reflection, the four main findings which we assert are important for developing AI systems are a change in mindset, being flexible to using both on-premises and cloud options, using education to support AI SD, and designating data as the Queen for AI.

A Mindset Change for Better Outcomes

The engineering and computer science disciplines are dealing with an old familiar mindset which is inhibiting progress and innovation. A change in mindset for how AI systems are developed can provide better outcomes for cases. With regard to cyber security for instance there should be better processes in place to identify secure solutions that support AI SD:

> *"Recently we have some more options like using the cloud we are using the Databricks, so doing some experiment. But still because [of] the customer security and privacy issue we cannot use customer data on the data in the cloud".* (Interview-5.3)

Reviewing how security measures are applied would provide a better approach than remaining rigid. While there is good evidence to support the current way of working i.e. no data leaks, no security incidents. There also needs to be a focus on how it is inhibiting progress and innovation. Cases in the study reported a common theme regarding cyber security compliance and the negative impact it has on getting access to new technology for experimentation. This results in cases being unable to effectively evaluate emerging AI technologies which may result in significant lost opportunity for innovative outcomes. While vendors are improving their technology and developing new capabilities there is a lack of urgency from cases to trial and experiment with them. Reasons may include the risk of failure resulting from being early adopters, or other more urgent priorities. A change in mindset and being more responsive and calculated when trialing emerging AI technology can provide better outcomes for cases and within the domain. It will ensure that cases achieve success with specific technologies earlier, and for any endeavors that result in failures; it enables cases to collaborate with vendors to work through lessons learnt so improvements can be implemented. The following are examples of data extracts related to mindset change. *"A mindset shift I should say that has to come with something like this. It is a new territory, and what we're doing to resolve it is just being transparent"* (Interview-1.3). *"Dweck's work demonstrates that success in human endeavors can be highly influenced by how one thinks. Someone who has a fixed mindset is less likely to succeed than someone with a growth mindset"* (whitepaper shared by Interview-2.1). In general a mindset shift for better outcomes is an area that cases must include in their AI development process. In all stages of AI SD, if an organizational process is halting progress this provides an opportunity for reassessment and improvement.

Being Flexible and Working with Both Cloud and On-Premises AI Technology

There are various widely used AI tools available on the market. This includes both on-premises and cloud options each with associated advantages and disadvantages. A well-known advantage of configuring AI tools on-premises is having complete control and ensuring the security and sovereignty of data assets. Conversely a widely accepted disadvantage is maintenance costs associated with managing on-premises infrastructure. Therefore a key accepted advantage of moving to the cloud in general and for developing AI systems is, that organizations are consumers of technology with the maintenance managed by the vendor. This makes it more economical for organizations to use cloud solutions. However, a key disadvantage of cloud technology options is that some cloud providers do not offer all services within the jurisdiction of their consumers (Baker et al., 2022). Examples of tools used for developing AI systems includes R, Python, TensorFlow (Chang & Jefford, 2020; Kaplan & Haenlein, 2020; Ong & Uddin, 2020). According to Gartner's recent report (Baker et al., 2022) the leaders for Cloud AI developer services are Amazon Web Services, Microsoft, Google, and IBM. This aligns with what was shared by participants in the interviews, for example, *"Mainly Python with TensorFlow, PyTorch, but also all the other packages you get with those"* (Interview-3.3).

With regard to being flexible and managing security the following was discussed:

> *"I think we have to be quite flexible because there's always a lot of new technologies that come about out there. But largely I think I'll focus on cloud technologies that can be translated to on-Prem installations and the reason for that is because, again mostly the data that we have played with are on-Prem or sort of within the specific tendency. Things like TensorFlow for example that I mentioned in AWS. They're very much more cloud strength. And I do envy those people who can use those cloud strength technologies that make good use of data. But without the ability for us to bring that down to an on-Prem installation, or you know your own private cloud tenancy installation, I think will be quite difficult".* (Interview-1.1)

It is therefore essential for organizations to be open to working with both on-premises and cloud AI technologies.

Education to Better Support AI System Development

Another common theme is that at present AI practitioners do not have AI education such as AI university qualifications for instance. This is mainly because until recently there was no such thing as AI qualifications. As a result AI practitioners today come from a variety of backgrounds and experiences and there is a diversity in the type of qualifications practitioners hold. This includes industry and higher education qualifications, ranging from the fields of law, business, computer science, among others. Examples include, Master of Business Administration, degrees in – history, computer science, software engineering, mathematics, actuarial, and econometrics. Industry qualifications include Microsoft Certification, and courses/certifications offered through Microsoft's AI Business School. It is critical to identify the key skills and experiences required for AI practitioners and develop qualifications (industry, higher education). To enable organizations to develop AI systems, it is important to establish standards for practitioners with regard to obtaining qualifications. Although a volatile and evolving area, currently there are several AI qualifications available. This includes free training courses which are available online. Companies such as IBM, Microsoft, Google offer several paid training and certification courses. Tertiary institutions are also offering AI related courses. For example, universities in Australia are offering qualifications such as data science, artificial intelligence, and machine learning. Cases reported university partnerships is part of their strategy to assist with developing AI systems. This allows organizations to get access to researchers and emerging AI technologies to experiment with, while also allowing universities to become better aware of industry requirements. *"Being able to partner with universities or organizations that are developing their people with these skill sets which are going to be very important in the future"* (Interview-1.3). Additionally it was stated that, *"One of the early departments that had a program of bringing in PhDs to support the Data and Analytics area. So we were closely linked in with some of the universities, particularly in Canberra and the like"* (Interview-3.1). Partnerships between industry and academia is a key area for AI to assist with training for experienced members of the workforce who transition into AI SD and to ensure the qualifications available for new graduates meet requirements of industry.

Data is Queen for AI System Development

In reference to the Chess board game where the queen is known as the most powerful piece, we argue that data is the most powerful piece for developing AI systems and designate it as the queen. As the most powerful piece in AI there is still opportunity for making data even more powerful. Cases in the research reported key issues which have a negative impact on developing AI systems. This included poor data quality, inadequate metadata, insufficient data lineage and tracking, and apprehensiveness to using too much data. *"We'll have the garbage in garbage out thing and you know, wack the AI on top of everything and just expect it to work. And all it'll do is be misled by our poor-quality data"* (Interview-1.4). It was also stated that, *"Data is always a challenge. And as I said, that's why I think that's where the next final ground is going to be. Because the quality of data, the accessibility of data, determines the success of the project"* (Interview-3.2). With large data holdings at their disposal organizations would benefit from treating data as the queen to ensure data flaws are improved and even better resolved through research and development. This relates to the mindset shift concept discussed above. The mindset that accepts the data issues as the norm is holding back progress of knowledge and development of better AI systems for society.

Theoretical Contributions

In this study, we have examined the 2PDT framework through case study research. The outcome of this examination highlighted the important role of people, process, data, and technology in the AI domain. This has contributed to a holistic view due to the characteristics of the 2PDT framework being, agility, rigor, dynamicity, and completeness. The agility comes from the expectation that the 2PDT can be easily integrated into existing organizational settings for developing AI systems. The rigor is provided by following an accepted research design which includes views of AI experts. Dynamicity is provided with continuous improvement being an important part of the framework to make it inherently adaptable to cope with change and ensure progress in AI SD practices. Finally, the completeness comes from bringing together a combination of existing theory and data collected from case studies.

With regard to people, the study highlights that there is a requirement for an increase in people with AI skills in the workforce. Partnerships with universities and investing in training and development have been identified as two important requirements which are essential for ensuring more people are equipped with important AI skills. With regard to process, publishing findings from organizational AI SD work was also found to be essential for the domain. This will encourage more organizations to share findings on a regular basis which will benefit the domain. With regard to data, the study will ensure organizations increase their efforts to ensure better quality data is captured and maintained. With regard to technology, the study will ensure risks associated with investing in inaugural technology are better understood. Given that AI technologies are evolving rapidly they have not been tried and tested effectively, as a result, organizations will not achieve the desired value from them unless they develop clear strategy to better inform technology selection decisions.

Practical Contributions

The agility and dynamicity of the 2PDT framework enables organizations to develop effective AI systems regardless of their AI SD maturity. The dynamicity through the continuous improvement process will ensure organizations learn from experience.

The study included cases from important fields including education, technology, law enforcement, healthcare, and academia. This demonstrates that the 2PDT can be applied in different fields, industries, and environments. Other examples of applicable fields where the 2PDT can be applied includes finance, sport, science, agriculture, and retail.

The study will also empower organizations to apply the framework and identify other areas of improvement related to their context. While empirical data was collected from Australian based organizations, other organizations from the Pacific Asia region and beyond will also benefit from the findings. We believe that the key finding of the study is that the 2PDT framework will improve organizational AI SD.

Conclusion

This research study employed a case study approach to explore how a framework can promote effective organizational AI SD. To achieve this a holistic framework for AI SD was conceptualized and examined from an organizational perspective. Interview participants included AI experts from various roles, and the thematic analysis approach was used for data analysis. This study was limited to 12 cases based in Australia (39 interviews, and 87 document reviews).

People are critical for effective system development, and they influence the quality and value in relation to processes, data, and technology. People's knowledge, experience, and skills enable development and adoption of processes to ensure effective organizational system development.

Strong processes reflect the knowledge and experience within an organization. Poor processes for system development provide a strong indication that the people within the organization are lacking the appropriate knowledge and experience, or that organizational processes may be inhibiting people to improve and introduce required changes.

It is critical for organizations to promote a culture that accepts data as the queen to ensure it is cultivated. This will ensure effective organizational AI SD and system development generally.

Technology is merely the instrument that relies on people, process, and data. Technology is not the foundation for system development, and it cannot independently promote development of effective organizational systems. People's knowledge and skills are critical for adoption and improvement of technology. Processes ensure appropriate and accurate organizational technology investments.

One limitation of the study was a lack empirical results from related studies into AI frameworks. While these theories and framework exist there is a lack of empirical results from testing and application of them. This makes it problematic to answer questions such as whether conceptual frameworks for AI account for more success, produce better outcomes, or provide specific benefits. Secondly, even though study participants were provided the participant information document which included details such as how the study would address confidentiality, anonymity, and data storage. Cases still expressed some concern and were unable to share documents which may have been useful for analysis and could have enriched the study findings. Cases mainly shared de-sensitized documents, and documents which are publicly available. To minimize the impact of these limitations, the study, recruited appropriate participants from different sectors, employed an appropriate methodology for data collection and analysis to ensure the empirical analysis have been appropriately explored and discussed.

There is opportunity for future work to study additional organizations, and to evaluate the 2PDT framework in other geographical locations and organizations. This will expand upon the content of this paper, contribute to the analysis and effectiveness of the 2PDT framework, and also to knowledge in the AI domain. There is also opportunity for future work to focus on application of the 2PDT framework in organizations to examine the results produced.

The examination of the framework and case study approach added valuable knowledge to the AI domain. In addition, we contributed to theory and practice by identifying requirements that organizations should consider in achieving better outcomes through AI SD.

Acknowledgements

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Appendix A

A case study protocol is essential for conducting case studies as it provides (1) the guardrails to keep the researcher(s) within the topic of the case study, and (2) it ensures precise planning and forethought (Yin, 2018, p. 94). This research study has followed the case study protocol below. It contains the overview of the theoretical approach, data collection procedures, protocol questions, data analysis procedures, and an outline regarding case study reporting.

Case Study Protocol

1. Undertake literature review to learn about the AI phenomena and theory
2. Develop 2PDT as a conceptual framework
3. Conduct pilot study to:
    a. Test and refine study design i.e. questions, methodology
    b. Understand what the collected data will look like
    c. Ensure the collected data is appropriate
4. Identify organizations and make contact seeking for participant volunteers and arranging time for interviews
    a. Data collection procedures
        i. Consent form endorsement
        ii. Name of sites to be visited, including contact person details
        iii. Data collection plan
        iv. Interview preparation work
        v. Document reviews including looking at reports and website for information on AI
    b. Interview Questions
        i. Based on organization’s context of AI
            1. Why is this organization investing in AI?
            2. How does this organization go about managing AI projects?
            3. What is the current situation of AI in the organization?
        ii. Based on 2PDT
            1. How does technology enable/inhibit this organization with management of AI projects?
            2. How do people factors (i.e. training, development, workforce management) enable/inhibit this organization with management of AI projects?
            3. How do data factors (i.e. quality, availability) enable/inhibit this organization with management of AI projects?
            4. How do internal/external standards/processes (i.e. information security, project management, policy development) enable/inhibit this organization with management of AI projects?
5. After completion of each case study, reflect on findings and analyze data
    a. Findings from government and industry cases
        i. Categorize based on 2PDT
        ii. Use appropriate coding technique
        iii. Summarize findings
    b. Empirical data analysis
        i. Analyze findings based on 2PDT
        ii. Use appropriate coding technique
        iii. Use appropriate coding technique for comparisons
        iv. Comparison of literature and empirical data
        v. Develop new themes from empirical data
6. Summarize findings and contribution to research objectives
7. Present papers in conferences and journals to get feedback
8. Incorporate feedback and produce final thesis

About the Authors

Sahber Monshizada is a final year PhD candidate at the University of Canberra. His research is focused on effective Artificial Intelligence system development. He is a previous graduate of the university having completed a Bachelor's and Master's of Business Informatics. His working career spans 18+ years and he is currently working as Data Management Assistant Director. Sahber's interests include building ethical and responsible AI systems, cyber security, getting the most out of data, developing and implementing technology strategy, and leading digital transformation through enabling technologies.

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