MAPPING ARTIFICIAL INTELLIGENCE AFFORDANCES FOR THE PUBLIC SECTOR

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ABSTRACT

AI technologies are becoming part of human life and bring a transformational impact. Many organisations have made AI technologies an integral component of their business models. The planning of AI in the public sector has also started to gain momentum. More than forty countries have launched national strategic AI plans, and dozens are devising them. AI deployment in the public sector is an emerging trend. There has been enormous ambiguity regarding AI planning, design, and deployment. Like other sectors, AI has a variety of affordances for the public sector. However, the critical issue has been to actualise AI's affordances so that they contribute to public value creation for public agencies. In this thesis, the affordance theory lens is used to explore AI affordance perception and actualisation for the public sector through three related studies. The perception of AI affordance is investigated in the first two studies. The third study designed and evaluated artefact for public agencies to actualise AI affordance.

Study 1 explores how AI affordances have been perceived at the national level. It analyses the national strategic AI plans of 34 countries and identifies the core priority areas for AI development, deployment, and AI governance. After identifying the AI affordance perception, Study 2 explores why these 34 countries have approached AI differently and how the contextual conditions (technical, social, political and economic factors) have contributed to actualising AI affordances. Study 3 focuses on AI affordance actualisation for the public sector by designing, demonstrating, and evaluating an artefact grounded on a business model canvas (BMC) template for public agencies.

The thesis answers what, why, and how questions about AI affordances in the public sector. By using a combination of data sources (primary and secondary) and employing a set of methodologies involving a qualitative approach, mixed-method research, and design science research methodology (DSRM), the thesis covers a variety of theoretical and empirical avenues. The theoretical contributions of the thesis demonstrate the knowledge of AI affordance perception and actualisation for the public sector and extend details on affordance theory in a public sector setting.

Each study contributes to the overall objective of exploring the affordances of AI for the public sector. Study 1 contributes to knowledge on the perception of countries about AI affordances through document analysis of national AI plans. This study also contributes to the public sector's strategic planning and policy analysis. Study 2 extends knowledge on AI affordance perception and actualisation of countries by comparing national AI plans and contextual conditions using signalling theory. This study develops an intention and veracity matrix for the claims made in national AI plans and validates them according to the contextual conditions of countries. Study 3 focuses on AI affordance actualisation by designing an artefact for public agencies. These studies extend knowledge on innovating business models of public agencies for AI deployment in a socially responsible manner. The thesis also offers several of societal and policy implications related to AI deployment and anticipates the future of AI in the public sector.

LIST OF PUBLICATIONS

Journal articles (Q1)

- **Fatima, S.,** Desouza, K. C., & Dawson, G. S. (2020). National strategic artificial intelligence plans: A multi-dimensional analysis. Economic Analysis and Policy, 67, 178–194. https://doi.org/10.1016/j.eap.2020.07.008
  The article included in the thesis (Chapter 3)

- **Fatima, S.,** Desouza, K. C., Denford, J. S., & Dawson, G. S. (2021). What explains governments interest in artificial intelligence? A signalling theory approach. Economic Analysis and Policy, 71, 238–254. https://doi.org/10.1016/j.eap.2021.05.001
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- **Fatima, S.,** Desouza, K. C., Buck, C., & Fielt, E. (2022). Public AI Canvas for AI-Enabled Public Value: A Design Science Approach (Accepted for publication in Government Information Quarterly, in press)
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- **Fatima, S.,** Desouza, K.C., and Dawson, G.S. (2022). Interpreting National Artificial Intelligence Plans: A Screening Approach for Aspirations and Reality (Accepted for publication in Economic Analysis and Policy, in press)

Peer-reviewed conference papers

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Other related industry publications

- **Fatima, S.,** Desouza, K. C., & Dawson, G. (2020, June 17). How different countries view artificial intelligence. *Brookings*. https://www.brookings.edu/research/how-different-countries-view-artificial-intelligence/
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- **Fatima, S.,** Desouza, K. C., Dawson, G. S., & Denford, J. (2021, November 10). The people dilemma: How human capital is driving or constraining the achievement of national AI strategies. *Brookings*. https://www.brookings.edu/blog/techtank/2021/11/10/the-people-dilemma-how-human-capital-is-driving-or-constraining-the-achievement-of-national-ai-strategies/
- **Fatima, S.,** Desouza, K. C., Dawson, G. S., & Denford, J. (2022, January 12).How countries are leveraging computing power to achieve their national artificial intelligence strategies. *Brookings*.

https://www.brookings.edu/blog/techtank/2022/01/12/how-countries-are-leveraging-computing-power-to-achieve-their-national-artificial-intelligence-strategies/

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AI	Artificial intelligence
BMC	Business model canvas
DSRM	Design science research methodology
PAIC	Public AI canvas

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Chapter 1: Introduction

Technology has played a vital role in human development (Garud & Rappa, 1994; Orlikowski & Scott, 2008). It can drastically transform the functions of societies (Barley, 1986; Burmaoglu et al., 2019; Cath et al., 2018; Leonardi & Barley, 2008; Solow, 1957). The functions of technology range from the automation of mundane tasks to autonomous systems that require little or no human intervention (Dwivedi et al., 2019). However, the potential of technology to transform is mainly dependent on the user's goals, and capabilities, and the interaction between these (Faraj & Azad, 2012; Oborn et al., 2021; Strong et al., 2014).

The possible benefits of technology are rendered through technical objects. Technical objects are material objects that establish an interaction between technology and the user (Volkoff & Strong, 2013). In information systems, the potential benefits of technology are called technology affordances (Anderson & Robey, 2017; Volkoff & Strong, 2013). Markus and Silver (2008) defined technology affordances as "the possibilities for goal-oriented action afforded to specific user groups by technical objects" (p.622). A technical object can offer all possible affordances, termed potential affordances, and are also known as functional affordances (Markus & Silver, 2008). However, the potential affordances do not guarantee results; instead, they offer potential benefits that might occur if a goal-oriented user actualises the technical objects (Faraj & Azad, 2012).

The evolution of information technology has happened over decades, from automating manual tasks to augmenting or replacing human activities through human-like cognitive systems called artificial intelligence (AI) (Dwivedi et al., 2019). AI technologies have been used in various contexts, such as machine learning, computer vision, speech analytics, and robotics and have been penetrating human lives at a fast pace (Berryhill et al., 2019; Zuiderwijk et al., 2021).

Like other sectors, the public sector has actualised technology affordances in various functions. After introducing the worldwide web in the early 90s, technology adoption in the public sector increased (Bekkers, 2003). In the initial stages of technology adoption, there were minor changes, such as maintaining government information in electronic formats (Dugan & Cheverie, 1992), designing websites (De Jong & Lentz, 2006), and technology-sharing among public agencies (Janssen, Chun, & GilGarcia, 2009). Later, the affordances of technology moved from automation and electronic communication to the online delivery of services, such as healthcare (Andersen et al., 2012) and e-justice platforms (Rosa et al., 2013). Since 2015, the digital innovation journey of governments has abundantly increased the application of AI (Levy et al., 2018).Currently, dozens of countries around the globe have released national strategic AI plans. These plans present countries' priorities for AI development, implementation, and governance (Fatima et al., 2020b). The use of AI for improving the lives of citizens has progressed (Chatterjee et al., 2018), for example, in the use of AI-enabled healthcare systems (Müller et al., 2020) and transportation management (Kouziokas, 2017).

There have been various cases of AI deployment in public agencies, such as using edge computing (a domain of AI applications) for smart parking and decreasing traffic congestion in Cologne, Germany. Cologne has been one of the most congested cities in Europe, with Germany facing severe issues of urban traffic and CO2 emissions. To overcome various climate protection and energy transition challenges, the SmartCity Cologne Program (SCC) was launched by the City of Cologne (Parker, 2020).

This project has collaborated with Rhein-Energie AG (Germany’s fifth-largest energy supplier) and Cleverciti (a parking solution provider). Around 100 smart sensors have been deployed in the heavily populated urban district of Nippes. The efficiency of this project has been high as no new resources were installed to place the smart sensors; instead these were placed on existing lampposts on the road. These smart sensors have collected real-time data and highlighted available parking spots using GPS signals and image processing coordination. This information has been analysed using edge computing, a domain of AI applications. One sensor, on average, can monitor 800 street parking spaces (Parker, 2020).

Similarly, the Bureau of Labour Statistics (BLS) in the United States of America (USA) started to use AI to code data. BLS has been the leading agency of the USA government in collecting statistics in the field of labour economics and statistics. Through the annual survey of occupational injuries and illness in the workplace, BLS has collected data from 200,000 businesses. Besides collecting and summarising injuries data, BLS also has informed companies and public agencies about why and how these injuries happened, who can use such insights to strategise the prevention of injuries. However, reading hundreds of thousands of survey responses was challenging for BLS staff. The staff was required to code the responses, such as different codes for the designation of the employee, type of injury, and affected body organ. The coding of information was a lengthy, mundane and uphill task to remember all the codes, and the probability of human error was also evident. In 2014, BLS started to use AI for coding, and the AI system for coding automation was deployed gradually, starting with the automatic coding of designations. Machine learning was the basis of this automation that learnt from data and improved over time. The gradual deployment of the system also indicated BLS's vision of learning from data over time (Partnership for Public Service, 2018).

AI-enabled systems in public agencies have not been limited to the mere automation of tasks to augment human capabilities. There also have been example cases where AI systems have been deployed with without or little human intervention, such as the deployment of self-driving trolleys for public transport in the city of Bryan, Texas, USA, which was approved by the City Council in September 2018, and begun in the spring of 2019. These trolleys were fully autonomous and staffed by two safety workers within the trolley, with up to four passengers in one trolley.

These trolleys made trips of eight blocks and stopped at five passenger stations. To navigate roadways, these electric trolleys utilised enormous input data from cameras and laser imaging, and detection and ranging (LIDAR) sensors in real-time, which allowed the self-driving trolley to navigate public roadways. The local government illustrated an appropriate risk management approach by deploying two human staff within the trolley. Professor Sariapalli, the lead researcher from Texas A&M University stated that he was interested in developing an AI-enabled public service where the data of the system design must be freely available to public officials so that the transparency of such systems could be increased and, resultantly, public acceptance and trust could also be gained (Bullock & Young, 2020). The realization of AI affordances with public acceptance and trust has been in the emergent phase and its materialisation has been mainly dependent on a deep understanding of AI affordances (Mora et al., 2021).

AI is a disruptive technology that has plenty of affordances for goal-oriented users (Achmat & Brown, 2019). Potential or functional affordances are in-built features that a technical object depicts. In comparison, affordance actualisation emerges from user and object interaction (Kude et al., 2018). Affordance actualisation is also named relational affordance (Anderson & Robey, 2017). The actualisation of technology affordances occurs when the user actualises the benefits of technology through the intention, capability, and other contextual elements (Mora et al., 2021). Like other technologies, the actualisation of AI technologies depends on how users' intentions, capability, and interaction combine together to benefit from these technologies.

1.1 Problem Description

There has been variety in how the public sector has intended to materialise AI affordances. It is essential to investigate how the public sector perceives and actualises AI, presented in the following section.

First, AI offers a variety of potential affordances; however, not all affordances have been actualised. Potential affordances are the properties of a technical object offered to potential users (Strong et al., 2014; Tim et al., 2018). For example, in the 2020 Tokyo Olympics (postponed due to Covid-19 and rescheduled in 2021), athletes with access to sports technology, such as 3D glasses, video analytics, and wearable tech, were better prepared to win gold medals (South China Morning Post, 2021). The properties of sports technology equipment are the functional affordances. However, only well-funded teams from developing nations were able to practice with such technologies (South China Morning Post, 2021). The actualisation of sports technology was impacted by the nations' contextual conditions, that is, an ability to fund the games. This example only covers the capability of users (nations) to actualise sports technology but there are a number of factors that impact on affordance actualisation based on users' intentions, capabilities and contextual conditions. The key point here is that potential and actual affordances vary for different users and there is little research on the topic (Dwivedi et al., 2021). Therefore, in this thesis the affordances of AI for public sector were investigated by first exploring the perception and then actualisation of AI.

Second, the differences in AI affordance perception presents countries' priorities about the use of AI. For example, some countries prioritise AI for agriculture (India AI Plan, 2018), while others intend to use it for aged care (Australia AI Plan, 2019).

Similarly, there have been differences in countries' priorities for AI, such as how various countries handle the governance and ethical issues related to AI are different across countries. Therefore, it is vital to investigate how various countries plan to actualise the affordances of AI.

Third, AI affordance actualisation has been impacted not only by affordance perception but also by the socio-materiality of technology (Mutch, 2013; Orlikowski & Scott, 2008; Senyo et al., 2021). According to socio-materiality theory, socio-material arrangements of users' environments shape technology affordance (Mora et al., 2021). Therefore, when identical technical objects are used in different contexts, the extent of actualisation differs and and also the benefits associated with technology. Strong et al. (2014) defined social arrangements as connecting social and material dimensions of technology deployment. When AI is viewed as a technical object for the public sector, socio-material factors play a vital role in AI actualisation. An exciting interplay between technology deployment and socio-material arrangements is considered in the thesis.

Fourth, AI deployment in the public sector needs to create public value. The public sector has used technical objects to create and maximise value (Makasi et al., 2020). However, the objective of public value creation is impacted due to two main reasons. 1) public agencies' readiness to adopt AI technologies requires attention (Buren et al., 2020; Montoya & Rivas, 2019). Public agencies are less flexible than private enterprises in developing capabilities for AI-enabled systems (Mikalef et al., 2021a). 2) AI is an emerging technology and there is no complete understanding of its potential and its consequences (Margetts & Dorobantu, 2019a). Despite advancements in AI-enabled systems, issues relating to ambiguity, opacity, disparate treatment, and the violation of privacy have continued to exist (Holmes et al., 2021; Schiff et al., 2021; Stahl, 2021). Considering the challenges associated with the use of AI systems, it is critically important to deploy AI so that it adds to public value. To address this issue, artefacts for public value creation using AI are also designed in this thesis.

Considering the issues discussed above, the problem statement of the thesis is:

There are differences among countries about AI affordance perception and actualisation. Various socio-political factors play a role in determining AI affordance and actualisation. AI perceptions vary amongst countries and these differences account for variety in AI actualisation in the public sector. To enable AI actualisation, artefacts that actualise AI need to be designed for the core objective of public value creation and maximisation.

1.2 Research Rationale

This section discusses why it is vital to investigate the problem statement formulated in the previous section. First, the use of AI systems in the public sector has been increasing (Zuiderwijk et al., 2021). Governments around the globe have employed various forms of AI-enabled systems to increase productivity and efficiency, and improve the quality of public services (Berryhill et al., 2019; Houser & Sanders, 2018; Mikalef et al., 2021a; Müller et al., 2020; Nikolaev et al., 2017). Some examples of AI use in the public sector have been in the Procurement Innovation Lab (PIL) of the United States Department of Homeland Security (Chenok, 2020) and the installation of AI-enabled cycling sensors to redesign road junctions (Lee, 2021). However, it is pertinent to remember that AI technologies have been emerging, indicating that governance-related challenges have existed (Holmes et al., 2021; Mikalef et al., 2019, 2021a). The implications of how a country should engage with an emerging technology, which has a faster pace of development than any policy process, have been challenging. Since the development and practical implications of emerging technologies such as AI have not been fully realised, the usefulness of these technologies in some domains has remained unclear. Therefore, it is essential to explore how governments intend to deploy AI.

Second, countries want to win the technology race (Castro et al., 2019; Schmidt & Allison, 2020). This race is based on the assumption that AI dominance leads to economic and military authority; nations have put severe efforts into deploying AI technologies (Kapetas, 2020). One example of such efforts has been to allocate significant budget slices for AI capability development (Coldewey, 2020; Cyranoski, 2018; Sinha, 2021). The AI race among countries can be viewed like an arms race between the USA and the Soviet Union. The production of nuclear weapons to win the warfare could now be related to AI technologies to gain technology dominancy (Pupic et al., 2018), where AI is the weapon (Straub, 2018). It is, therefore, crucial to investigate how significant initiatives that have been taking place or are likely to occur in the near future to form the technology landscape.

Third, the use of AI can result in unintended outcomes (Yampolskiy, 2019). For example, an AI system can malfunction or fail to perform on technical grounds, that is, system design issues, poor quality of data or algorithmic biases. (Allyn, 2020; Barton, 2019; Charette, 2018; Kordzadeh & Ghasemaghaei, 2021). One example of unintended outcomes is the killing of a pedestrian by an autonomous car due to the system's inability to recognise humans (Newcomer, 2018). Similarly, the use of AI-enabled systems in the public sector has also witnessed malfunctioning incidents. A few such examples are the use of a facial-recognition tool by metropolitan police that resulted in racial bias for non-white people (Margetts & Dorobantu, 2019a), the use of an automated welfare debt recovery process known as "Robodebt" that caused illegal, unfair and biased outcomes with the cost of public trust (The Guardian, 2021b), and the use of a countrywide automated payroll system that made wrong payments and deductions (Charette, 2018). These are a few example cases where AI systems did not work as intended and caused considerable losses in the public sector.

Besides developing fault-free AI systems, the public sector has faced pressure from an increasing number of regulatory guidelines (Marcia & Desouza, 2021; Yeung, 2020). Considering these challenges, it is essential to understand the dynamics of AI affordance for the public sector and find means to deploy AI to maximise the core objective of public value creation for public sector agencies.

1.3 Research Gaps

This section presents the research gaps found in the literature that led to this thesis's development.

1.3.1 Gap 1- Limited Literature on AI Affordances

First, AI-based systems have been emerging technologies whose affordances have not been fully realized. In a systematic review of AI affordances for business innovation, it was found that AI has been used for automating business processes, customising end user interaction, predicting and preparing for changes, augmenting workforce, assisting decision making, improving risk management and developing intellectual properties (Achmat & Brown, 2019). This review also identified areas for future research on AI affordances. Due to inconsistent definitions of AI, the literature on AI affordances was limited. Moreover, the literature has mixed the term AI and AI-related applications (big data, IoT, smart systems etc.); therefore, it has become difficult to cover the affordances of the umbrella term AI. This thesis includes the affordances of AI as an umbrella term and defines AI as a set of technologies that exhibit human-like or exceeding human capabilities. Further details are given in Chapter 2 (see Section 2.1.2).

Second, the literature on AI affordances has suggested that AI-related risks have not been fully understood (Bonnín Roca et al., 2017). In the light of potential benefits of AI based systems, the related risks must not be ignored (Floridi et al., 2018a; Marr, 2018; Turchin, 2019; Turchin & Denkenberger, 2020). Therefore, this thesis highlights the feasible use of AI affordances, including potential benefits and associated risks in a public sector context.

1.3.2 Gap 2 - Limited Literature on AI Affordances in the Public Sector

The other research gap is related to AI affordances in the public sector. First, The adoption of AI in the public sector is slower than the private sector (Desouza, Dawson, et al., 2020) and consequently there are fewer evidence of empirical research on this topic (Margetts & Dorobantu, 2019a; Mikalef et al., 2021a; Montoya & Rivas, 2019). By specifying AI affordances, this thesis fills the research gap to expand knowledge on AI in the context of public sector. There has been less specific knowledge and tools of AI affordances materialization in the public sector (Aoki, 2020; Wirtz et al., 2020; Wirtz & Müller, 2018). It is, therefore, important to explore knowledge on AI in the public sector.

Second, the review of literature also indicated that there was a limited understanding of the multifaceted implications of AI (affordances and associated risks) for society, economies, ethics and politics (Floridi et al., 2018a; Jobin et al., 2019; Makridakis, 2017; Shrum et al., 2019) This thesis, therefore, focused on multiple implications of AI and covered a broader perspective of societal, political and ethical considerations.

Third, it was evident that existing research on AI topics and its applications have focused on the technical dimensions of AI systems, such as system design components and processes (Aoki, 2020). Such research falls into the computer science domain and implies a highly technical knowledge base. However, there has been a scarcity of research on AI policies, deployment and governance (Agarwal et al., 2016; Agarwal, 2019; Barton, 2019; Burrell, 2016; Danks & London, 2017; Khalyasmaa & Eroshenko, 2017). Based on these research gaps, this thesis focused on exploring the implications of AI affordances.

1.4 Research Questions

The problem statement points to the over-arching research objective to enhance the understanding of AI affordances for countries, and subsequent public sectors; specification follows:

How does AI affordance function in countries and the public sector?

The secondary research questions are:

RQ 1: What are the AI affordance perceptions across nations?

RQ 2A: What have been the underlying socio-political factors that have caused differences between AI affordance perception and actualisation among countries?

RQ 2B: Why have the underlying socio-political factors caused differences between AI affordance perception and actualisation among countries?

RQ 3: How can AI affordance be actualised to create public value?

1.5 Research Significance

Recent literature that has used the technology affordance lens has investigated technology either as an overall digital system (Chatterjee et al., 2021; Kummitha, 2020; Mora et al., 2021; Senyo et al., 2021) or used one application of the technology system, such as blockchain (Du et al., 2019), social media (Chen et al., 2016), and telemedicine (Oborn et al., 2021; Thapa & Sein, 2018). By pioneering the use of a technology affordance lens to view AI-enabled systems and describing the socio-materiality of AI technologies in the public sector, this thesis informs the technology management literature and practice.

1.6 Thesis Outline

Three related studies that uncover the phenomenon of AI in the public sector and governments at large were used in this thesis. Three peer-reviewed journal articles (Studies 1-3) make up this thesis in the following chapter structure:

- Chapter 2: Literature Review
- Chapter 3: AI Policy Analysis

  Fatima, S., Desouza, K. C., & Dawson, G. S. (2020). National strategic artificial intelligence plans: A multi-dimensional analysis. Economic Analysis and Policy, 67, 178–194. https://doi.org/10.1016/j.eap.2020.07.008
- Chapter 4: Exploration of AI Interests

  Fatima, S., Desouza, K. C., Denford, J. S., & Dawson, G. S. (2021). What explains governments interest in artificial intelligence? A signalling theory approach. Economic Analysis and Policy, 71, 238–254. https://doi.org/10.1016/j.eap.2021.05.001
- Chapter 5: Public AI Canvas Design and Evaluation

  Fatima, S., Desouza, K., (2022). Public AI Canvas for AI-Enabled Public Value: A Design Science Approach (Accepted for publication in Government Information Quarterly)
- Chapter 6: Discussion and Conclusion
- References
- Appendices

1.7 Overview of the three studies

This thesis by publication includes three studies that address the research questions established in the previous sections. All of the studies share the underlying theme of AI affordance perception and the actualisation of nations in the public sector context, as explored in the literature review. The studies thematically progress towards the main research question and the three subsidiary questions.

The research questions are answered through three related studies. Publication titles and overviews of studies are given below.

RQ 1: What are the AI affordance perceptions across nations?

RQ 1 is answered through Study 1 (see Chapter 3), titled:

National strategic artificial intelligence plans: A multi-dimensional analysis.

Overview of Study 1:

This research question explores the perception of governments about AI affordances. The study presents the significance of AI as part of a national agenda. Considering national AI plans as an integral component of the national agenda, this study used these plans as the dataset. The study adopted a qualitative research methodology to explore what these plans indicate about a country’s perception of AI affordances. By conducting a content analysis of national AI plans using NVivo 11, the study presented common themes and concepts among these plans. The study covered the presence and absence of the common themes and concepts among the plans and identified comprehensively crafted national AI plans.

RQ 2A: What have been the underlying socio-political factors that have caused differences between AI affordance perception and actualisation among countries?

RQ 2B: Why have the underlying socio-political factors caused differences between AI affordance perception and actualisation among countries?

RQ 2A and 2B were investigated through Study 2 (see Chapter 4) of the thesis titled “What explains governments interest in artificial intelligence? A signalling theory approach”.

Overview of Study 2:

The objectives of Study 2 were to, 1) find the underlying factors that cause the differences between countries in AI affordances perception and actualisation and 2) validate the claims made in the plans with existing contextual conditions. This research question explored the differences between AI affordance perception and the actualisation of countries. After finding common AI themes in Study 1, Study 2 explained why there was a difference among countries in AI affordance perception and actualisation. It used the lens of signalling theory to view national AI plans as signals by countries. The study builds on the narrative that the intention and veracity of these signals would yield greater insights into countries’ perceptions and actualisation of AI affordances. The study uses a mixed-method research design named fuzzy set qualitative comparative analysis (fsQCA), where two sets of data (conditions and outcomes) are required. Study 2 uses the contextual conditions of countries (political, economic, social and technological factors) as one set of data and partially depends on Study 1's findings for the outcome data.

RQ 3: How can AI affordance be actualised to create public value?

RQ 3 is answered through Study 3 (see Chapter 5) titled “Public AI Canvas for AI-Enabled Public Value: A Design Science Approach.”

Overview of Study 3:

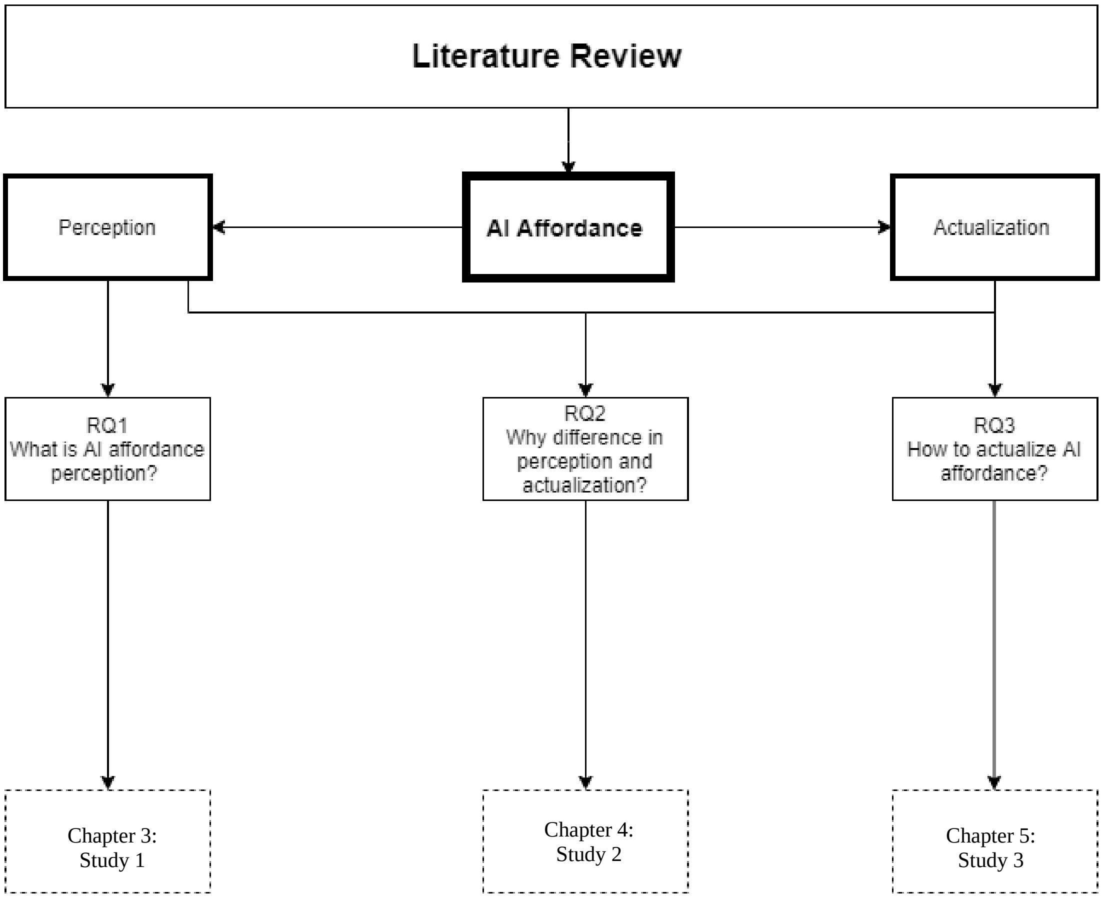
This study designed an artefact named public AI canvas (PAIC) for AI-enabled value creation in public agencies through design, demonstration and evaluation following the design science research approach. This study considered the issues related to AI-enablement, public value and social guidance for AI deployment in public agencies through three distinctive layers. The designed artefact was empirically validated in two steps, that is, demonstration of the artefact on an existing case study from Partnership for Public Services and conduct of 15 expert interviews to evaluate the artefact’s completeness, its fidelity with the real-world, its internal consistency, the level of detail and robustness. The findings of empirical validation indicated the agreement of expert interviewees on three layers of the artefact and the respective elements.

1.8 Linkage between Publications

The placement of studies to address the research questions is shown in Figure 1-1.

As defined in the previous section, the three research questions were answered through three related studies. Regarding the relatedness of the studies, it is pertinent to mention that Studies 1 and 2 are closely related. Study 2 uses the findings of Study 1 (dataset for fsQCA), and also investigates the differences among national AI plans as found in Study 1. However, Study 2 uses the lens of signalling theory to contribute to the thesis's overall objectives. Study 3 uses the design science research methodology (DSRM) to design the artefact by completing all stages of DSRM including demonstrating, evaluating, and communicating the designed artefact.

Figure 1-1 *Thesis Structure*



1.9 Summary of Chapter

This chapter began with a brief overview of the technology evolution and its impact on human lives in all facets. Artificial intelligence is presented as a disruptive set of technologies that offers various affordances. Following this, the chapter narrowed to focus on the affordances of AI for the public sector. By highlighting the increasing interest of governments in AI deployment, issues associated with such deployment are shown. Finally, this chapter presents how the problem is addressed through three related studies.

Chapter 2: Literature Review

The literature review chapter provides a background of the overall thesis theme. The chapter has three sections. The first section presents the evolution of technology management in the public sector, with a summary of how the public sector has embraced digital technologies over time. It concludes with a definition of artificial intelligence and examples of its use in the public sector. The second section describes the role of technology affordance theory in this thesis. Next is a presentation of the background of affordance theory and its variant, technology affordance theory. Then, AI is conceptualised through the lens of technology affordance theory. The third section presents more specific literature and extends details on the affordances of AI for the public sector. Next, the summary of the literature on AI actualisation, and defining the objective of public value creation through AI are presented. Finally, Section 3 presents a discussion of innovation in the business models of public agencies for AI deployment. The literature review chapter consists of seminal work, illustrative scenarios, and the identification of gaps in the field.

2.1 Technology Management in the Public Sector

Technology disruptions have been taking place on a large scale. Since the introduction of mainframe computers in the 1960s, technology waves, such as the internet, big data analytics, machine learning, natural language processing, and artificial intelligence have penetrated human lives on individual, community, and society levels (Agarwal, 2018; Dwivedi et al., 2019). The public sector has also experienced technology waves (Fishenden & Thompson, 2013; Gagliardi et al., 2017; Gil-Garcia et al., 2018; Heijlen et al., 2018). However, the pace and scale of technology adoption in the public sector has not been as rapid and extensive as for the private sector (Androutsopoulou et al., 2019; Berryhill et al., 2019; Mikhaylov et al., 2018a). Therefore, the literature on technology management in the public sector is also scarce (Mikhaylov et al., 2018a).

2.1.1 Digital Evolution of the Public Sector

Public sector agencies have gone through a digital evolution at the national, state, and local levels (Fishenden & Thompson, 2013; Gil-Garcia et al., 2018). Janowski's (2015) four-stage model of digital evolution in the public sector comprises digitisation, transformation, engagement, and contextualisation. The first stage in the digitisation model does not require any transformations in existing systems or practices; it solely focuses on automating the existing processes for improving the internal working of an agency. With limited offerings for the public sector, it could be converting agency information into digital formats (Dawes et al., 2004). Transformation brings technology-enabled changes in the administrative operations of public agencies. This stage aims for transformation in the way agencies interact with external actors, for example, the inter-municipal collaboration between agencies for e-government (Ferro & Sorrentino, 2010).

The engagement stage focuses on establishing agency presence among other agencies, citizens, or businesses through technology adoption, for example, engaging citizens through electronic communication channels (Cegarra-Navarro et al., 2014; Teerling & Pieterson, 2010). The fourth stage, contextualisation, builds on the previous three stages of digital evolution by contextualising digital government initiatives by engaging countries, cities, and communities. All processes outlined in the prior stages are fulfilled, for example, automation of the processes, internal working transformation, and relevant stakeholders' engagement. Governments align their technological initiatives with long-term strategic objectives, such as economic development and socio-economic impact assessment (Cordella & Bonina, 2012).

The digital evolution of the public sector is discussed in e-government models. For example, Layne and Lee (2001) presented four levels of an e-government model. The first level deals with cataloguing, with the government agencies communicating through websites (Layne & Lee, 2001). In the second level, online transactions are supported between government agencies and citizens, businesses, or other government agencies. In the third level, related government agencies integrate operations with other government agencies. The fourth level suggests that various government agencies horizontally integrate to facilitate activities between government and non-government agencies (Layne & Lee, 2001).

Some scholars have discussed digital technologies in cost savings and efficiency in public sector agencies (Behn, 1998; Bekkers & Homburg, 2007; Dunleavy et al., 2006; Gil-Garcia et al., 2018; Heeks & Bailur, 2007). However, others have presented digital technologies in public service design and delivery (Bertot et al., 2016; Chen et al., 2019; Lindgren & Jansson, 2013; Makasi et al., 2020; Mehr, 2017). The use of digital technologies in public services is referred to as ‘digital era governance’, which depicts the transition of industrial societies to online societies (Dunleavy & Margetts, 2010; Fishenden & Thompson, 2013).

The adoption of digital technologies in the public sector has been embedded through organisational changes. Literature has suggested that information and communication technology (ICT) has been one of the most prominent organisational changes in the public sector (Chadwick & May, 2003; Dunleavy et al., 2006; Fountain, 2003). ICT offers web-based technologies and internet applications to facilitate one-stop public services where citizens can interact electronically. It has also played a significant role in modernizing the internal work of the public sector. Therefore, ICT has also been attributed to increasing the performance and delivery of public services (Barbosa et al., 2013). The public sector also has been criticised for decentralised ICT initiatives and a lack of systematic methods to launch ICTs (Bekkers & Homburg, 2007). Besides presenting the usefulness of ICT for public services (Cordella & Bonina, 2012), many e-government studies have focused on how ICT use can harm the traditional value of public services (Bannister & Connolly, 2014). The traditional value of public services by Kernaghan (2003) was divided into four groups, these are, ethical, democratic, professional, and people.

Discussions on transparency (Bannister & Connolly, 2011; J. C. Bertot et al., 2010; Relly & Sabharwal, 2009), fairness, and honesty (Ebbers et al., 2008, 2016; Warren, 2007) of ICT in the public sector have gained attention over time. However, the probability of technologies damaging public interest has been primarily determined by the extent of human intervention (Sifakis, 2019). For example, ICT or other technologies have been used as a support tool to facilitate or augment human capabilities, for example, to increase efficiency (Ranerup & Henriksen, 2019) and accuracy (Ivanović, 2012), possess low autonomy. A technology-enabled system's autonomy is defined by its capacity to achieve coordinated goals with or without human intervention.

With the advent of intelligent machines, big data analytics (Ajana, 2015; Houser & Sanders, 2018), and complex algorithms (Agarwal et al., 2016; Agarwal, 2019), artificially intelligent systems have gained a high level of autonomy (Brkan, 2019). Therefore, fully autonomous systems can learn, reflect, and self-adapt to achieve coordinated goals without human intervention (Sifakis, 2019). The autonomy of artificially intelligent systems is subject to opacity, fairness, and accountability (Burrell, 2016; Engin & Treleaven, 2019; Lepri et al., 2018b). Recent literature has highlighted the contradictions between public value and autonomous systems in the public sector by highlighting Moore's (1995) public value dimensions. The inherent opacity of autonomous systems has been discussed as a threat to various dimensions of public value, such as fairness, ethics, transparency, explainability, and accountability (Desouza, Dawson, et al., 2020; Mikalef et al., 2021a; Misuraca & Viscusi, 2020; Toll et al., 2020).

Irrespective of the system autonomy level, the digital evolution of the public sector has faced challenges. For example, citizens' increased use of online public services enabled by digital technologies have not been welcomed (Hung et al., 2006). Most of this reluctance of citizens has been attributed to the uncertainty of outcomes that citizens sought about using technologies (Lamberti et al., 2014). The pace of digital evolution in the public sector also has been impacted by their ability to develop digital capabilities. The existing structures or processes are likely to become irrelevant for advanced technologies such as AI (Agarwal, 2018). The discussion on the challenges of digital evolution in the public sector has been extensive in the literature (Agarwal, 2018; Busuioc, 2020; Desouza, 2018; Desouza, Dawson, et al., 2020; Mikhaylov et al., 2018a; Wirtz, Weyerer, & Geyer, 2019). However, despite this extensiveness, there remain issues that are insufficiently understood.

2.1.2 Defining Artificial Intelligence

To understand the AI potential, defining AI is essential. Despite decades of work on AI, there has been no universally accepted definition of AI so far. However, exhibiting human-like intelligence is a common feature postulated by most definitions (Wirtz, Weyerer, & Geyer, 2019). Some scholars have defined human-like intelligence as machines' ability to learn and do things that only humans do (Adams et al., 2012; McCarthy et al., 2006), while other scholars have defined AI as a system of technologies that can perform beyond the abilities of humans (Grace et al., 2017). For example, AlphaGo, an AI-based application, defeated a world champion by self-learned moves (Silver et al., 2017).

Literature has suggested two broad AI categories: strong or general AI and weak or narrow AI. The first category, that is, strong AI, suggests that AI can match or surpass human cognitive capabilities (Berryhill et al., 2019), for example, AlphaGo. On the other hand, weak AI presents the distinct potential of machines. For example, weak AI enables humans to do repetitive tasks efficiently and accurately. More specifically, weak AI augments human capabilities to perform a task but does not overpower them. This thesis includes both weak and strong AI systems deployed in public agencies. Since AI deployment is in the embryonic phase in some countries, it is pertinent to include both categories of AI systems for the scope of this thesis.

Recent literature suggests AI is an independent system that uses principles to learn from external data to produce outcomes (Kaplan & Haenlein, 2019). However, previously, AI systems have been discussed as computing systems that work through big data and algorithms (Russell et al., 2010). The commonality of opinion prevalent among AI scholars is that the capability of AI systems is increasing. This progression has led to investigating autonomous systems, chatbots, medical diagnoses, system development, and use cases (Dwivedi et al., 2021). Dwivedi et al. (2021) segregated AI research into three themes: AI and decision-making (Abarca-Alvarez et al., 2018; Kahn, 2017); AI application domains (Dash et al., 2019; Mikhaylov et al., 2018b; Nikolaev et al., 2017); and data and information (Xu et al., 2019; Zheng et al., 2016). Their comprehensive review presented plenty of future research agendas for AI, including AI and strategic decision-making, AI policy and economy, and regulatory implications for AI.

The promises of AI for the public sector are numerous. The increasing use of AI in the public sector has intrigued governments worldwide to adopt AI systems (Zuiderwijk et al., 2021). The induction of AI-enabled systems can be seen in all public sector ecosystems, such as public service provision (Montoya & Rivas, 2019; Toll et al., 2019), efficiency gains in internal working (Niaounakis & Blank, 2017; Zarsky, 2016) forecasting, and prediction (Athey, 2017; Margetts & Dorobantu, 2019a) law enforcement (Alarie et al., 2018; Sousa et al., 2019), and algorithmic decision-making for policy design (Bayamlıoğlu & Leenes, 2018; Engin & Treleaven, 2019; Valle-Cruz et al., 2020).

Although AI research has a long history (Horowitz, 1978; Lynch, 1996; Maybury, 1990), it has gained considerable attention in the public sector in recent years (Aoki, 2020; Kuziemski & Misuraca, 2020; Zuiderwijk et al., 2021). The greater interest in AI research can be attributed to the associated challenges of AI in the public sector. First, as AI systems have become more complex, the opacity in system design and outcomes also has increased (Wirtz et al., 2020; Zuiderwijk et al., 2021). Second, using AI systems in the public sector has decreased citizens' trust instead of increasing it (Sun & Medaglia, 2019). Concerns related to data privacy (Brkan, 2019; L. Yang et al., 2018), and biased and unfair treatment (Engin & Treleaven, 2019; Kuziemski & Misuraca, 2020) have been explored by scholars. Furthermore, challenges, such as a lack of accountability in AI systems, have raised additional concerns for AI deployment in the public sector (Busuioc, 2020; Vogl et al., 2020; Wirtz et al., 2020). Despite the hype for AI transformations that are likely to happen in the public sector, there is an obvious need to explore the risks and challenges associated with AI deployment.

This section presented an overview of the digital evolution of the public sector. It briefly summarized the technology adoption process from automation of tasks to the launch of autonomous systems for creating public service. The section also presented multiple views on the definition of AI, and which view this thesis intends to use. Finally, the section highlights the benefits and challenges associated with AI deployment and identifies the need to explore further.

2.2 Affordance Theory

James Gibson, an ecological psychologist, defined the concept of affordance by highlighting how various species perceive their environment. He explicated affordance as a complementary relationship between the environment and animals. According to Gibson (1979), human beings identify environmental clues, such as substances, surfaces, and places, and generate environmental affordances. Gibson's (1979) affordance theory was extended by Norman (1988) when he connected environmental affordances to material artefacts. In his book *The psychology of everyday things*, Norman (1988) differentiated between actual and potential affordances. Actual affordances are created during the design of material artefacts while potential affordances depend on how users perceive and use the artefacts.

From the 1980s to the early 2000s, there has been significant work on differentiating between the design and user affordances of technology. For example, Orlikowski (1992) presented the concept of the duality of technology. According to the duality of technology, two modes of technology were identified: the design and user modes. The design mode refers to the structural properties of technology, whereas the user mode is related to human interaction with technology. Similarly, Suchman (2007) presented the idea of human-machine interaction to gauge the affordances of technology for humans.

The formal application of Gibson’s (1979) affordance theory to technology affordance has been attributed to Markus and Silver (2008), which explained the relationship between technologies and actors. Technology affordance is a variant of James Gibson’s (1979) affordance theory. The notion of technology affordance does not belong to actors or technologies independently; instead, it is a combination of actors and their perceptions of the technology (Parchoma, 2014). The affordances of technology exist; however, actors must exhibit capabilities and goals to actualise technologies. Thus, actors are named goal-oriented actors; hence, the user/actor cannot benefit from technology without goals to materialise technology (Hutchby, 2001; Markus & Silver, 2008). The artefacts through which technology exhibits potential to address a need are called technical artefacts (Leonardi & Barley, 2008). Similarly, the entities with needs that technical artefacts have the potential to address are called goal-oriented users (Markus & Silver, 2008). Technology affordance, as defined above, is the action potential of a technology offered via technical artefacts for a goal-oriented user (Hutchby, 2001; Markus & Silver, 2008).

The design and user modes of technology, as presented by Orlikowski (1992), have been updated in recent literature as potential and actual affordances. Potential affordances refer to affordances embedded during design (Strong et al., 2014; Tim et al., 2018), whereas actual affordances emerge from goal-oriented actors’ interaction with technical artefacts (Zheng & Yu, 2016).

2.2.1 Conceptualizing AI Through the Lens of Affordance Theory

Technology's potential usefulness (affordance) is rendered through a technical artefact that enables users to interact with technology (Mora et al., 2021; Tim et al., 2018; Zheng & Yu, 2016). Technical artefacts are subject to advancement in their design, functions, and outcomes. The capabilities of these artefacts cover a wide range, from automation tools to autonomous systems. Artificial intelligence technologies (AI) are among the most advanced forms of technology nowadays (Berryhill et al., 2019). By employing the lens of technology affordance theory, AI is defined in this thesis as a technical artefact with various potential and actual affordances.

2.2.1.1 Potential Affordances. Potential affordance, the set of features inscribed during technology design, increases when technology becomes advanced (Chambers, 2004). Thus, the potential affordance of AI is the set of potential actions that a goal-oriented actor might make to use AI (Du et al., 2019; Markus & Silver, 2008; Strong et al., 2014). Technological advancement extends the use or understanding of technology artefacts, devices, products, or processes (Serap & Gulsun, 2019).

2.2.1.2 Actual Affordances. The flexibility in the deployment of technology creates different outcomes of technology. The actual potential of technology remains constant (Senyo et al., 2021; Strong et al., 2014). Research has shown AI’s ability to transform societies and nations (Desouza, 2018; Dwivedi et al., 2021; Makasi et al., 2020). However, how AI systems are actualised in various contexts makes a difference in AI affordances. It is, therefore, essential to consider the contextual factors that impact the process of AI actualisation (Mora et al., 2021). AI affordance is mainly dependent on socio-material components. According to socio-materiality theory, social dynamism shapes the affordances of technology. Similar technologies, when deployed in two different social contexts, the affordances are not the same (Leonardi & Barley, 2010). Similarly, AI’s deployment in different contexts yields non-identical outcomes (Du et al., 2019).

2.2.1.3 Difference Between Potential and Actual Affordances. It is vital to distinguish between the potential and actual affordances of AI. For example, the potential affordance of virtual agents is to interact with users by featuring speech analytics and natural language processes data input (Zheng et al., 2018). However, how users actualise the potential of virtual agents is AI actualisation.

The relationship between the technology advancement level and potential affordance is directly proportional, that is, the potential affordances of technology increase as technology advancement increases (Mora et al., 2021). However, the actual affordance and technology advancement level have not been found to have a linear relationship. Therefore, implementing technology alone would not result in producing the benefits of technology.

Studies have shown that to benefit from technology, it is important to align the socio-material factors with technical artefact/object (Mora et al., 2021). It is imperative to develop an alignment between user goals, capabilities, and contextual factors to yield the benefits of technologies. Such alignment has been named affordance potency (Anderson & Robey, 2017). Although Anderson and Robey (2017) defined affordance potency for individuals and how they work in organisations, the term can be conceptualised for any unit (goal-oriented user), depending on its abilities and contextual factors.

The global pandemic of Covid-19 presents a recent example of how potential and actual affordances of technology have resulted in different outcomes. Many countries with identical technology infrastructures handled the pandemic in quite different ways. ICT-based contact tracing and surveillance systems have been in place in several countries. However, logistical barriers, overcomplicated bureaucracy, and a lack of transparency have hindered the use of this artefact in some countries (Mora et al., 2021). Despite having identical functional affordance, there have been huge differences between the performance of countries in actualising the technical artefact for handling the global pandemic (Mora et al., 2021).

As mentioned in the example of countries' responses to the global pandemic of Covid-19, not all countries with high potential affordances performed well in handling the pandemic using technology. However, some other countries with relatively low potential affordances successfully actualised technology to control pandemic repercussions. Such insights lead to the exploration of what, why, and how contextual factors influence the actualisation of technology.

2.2.1.4 Why the Affordance Lens? The understanding of the potential benefits of AI has been an emerging discipline that has not been fully explored so far. There have been debates about the potential benefits, opportunities, risks, and threats associated with AI deployment (Dwivedi et al., 2021; Zuiderwijk et al., 2021). Similarly, affordance theory outlines the possible benefits of an artefact whose benefits have not been fully identified. The affordance lens is used to explore and materialise the potential benefits of emerging technologies (Mora et al., 2021; Senyo et al., 2021), for example, blockchain technologies (Du et al., 2019; Ostern & Rosemann, 2020).

Therefore, in this thesis, an affordance lens is used to predict the actualisation of AI for the public sector.

Moreover, the affordance theory in the ecological context has been discussed as a transition from affordance perception to action (Michaels, 2000). The affordance lens is a suitable approach to explore AI affordance perception from the national AI plans level to AI affordance actualisation at the public agency level. Public agencies, as operationalised units of government structure (Thomas & Poister, 2009), actualise the strategic plans.

2.3 AI Affordances Materialisation for Public Agencies

The concept of public value refers to the actions performed by the government for citizens through public services, regulations, and law (Moore, 1995; Pang et al., 2014). The underlying philosophy of public value is that instead of following the politically established public service protocols, the public managers should use innovative ways to offer the best services to the public (Davies & Williams, 2003). Moore (1995) suggested that public managers and officials can offer multifaceted benefits to the public by 1) increasing the quality or quantity of public services, 2) reducing the cost of services, 3) anticipating citizen expectations, 4) making public agencies' operations transparent, and 5) increasing the responsiveness to citizens' communication.

AI application in the public sector has gained significant attention (Desouza, Dawson, et al., 2020), and debate on its potential in the public sector also has increased (Desouza, 2018; Wirtz, Weyerer, & Geyer, 2019). Among the applications of AI in the public sector, process automation, predictive analytics, and virtual agents have been more significant in numbers (Wirtz, Weyerer, & Geyer, 2019). The use of AI applications in the public sector has been gaining attention from academics and practitioners (Makasi et al., 2020; Mehr, 2017; Power, 2016).

The challenges associated with AI use in the public sector have been acknowledged among scholarly communities (Berryhill et al., 2019; Desouza, 2018; Mikalef et al., 2021a; Wirtz, Weyerer, & Geyer, 2019). There are numerous cases of AI use in public agencies. For example, the Office of Compliance Analytics, U.S., has detected tax fraud using algorithms (Houser & Sanders, 2018), and India has predicted water demand and supply patterns for a significant part of its agricultural land

(Merchant et al., 2014). There also have been examples where AI applications in the public sector have generated tremendous results for efficient public services. For instance, a disease surveillance system designed with machine learning algorithms (MLA) in Hampshire, England resulted in more than a 90% reduction in norovirus outbreaks (Mitchell et al., 2016). Similarly, the Santa Cruz Police Department in California, the U.S., used AI-based analytics tools to predict criminal acts and achieved a 27% reduction in the crime rate within a short period (Filipovitch, 2017). Furthermore, the Australian Tax Office launched a chatbot to answer citizens' queries about taxes, and surprisingly, the first contact resolution rate increased to 80% (Mohasses, 2019). Similarly, the U.S. Coast Guard adopted AI applications to generate satellite images of vessels that might be involved in unlawful acts (Sagawa et al., 2019). Also, the National Aeronautics and Space Administration (NASA), the U.S. federal agency for space exploration, has used AI to detect planets in telescopes (Levy et al., 2018).

These are instances where AI applications have exhibited significant benefits to the public sector. However, challenges, such as data integration across agencies, resistance to change, algorithmic bias, and citizens' expectations of transparency (Dwivedi et al., 2021) also have been associated with applying AI in the public sector. AI-enabled systems have greater affordances for the public sector but identifying 'what' and 'how' to get the maximum from these technologies requires investigation. For example, AI-enabled systems offer benefits, such as automating public services, using chatbots and intelligent assistants for public engagement, and robotic advisors to support civil servants. (Engin & Treleaven, 2019). Materializing the affordance of technologies depends on the suitability with actor goals and the intended outcomes (Mora et al., 2021; Orlikowski & Scott, 2008).

It is essential to understand why and how some affordances of AI are actualised and others are not. The past research shows no indication of how AI affordances are selected by public agencies. For example, the affordances of predictive maintenance techniques will be of great usefulness for aircraft and road safety (Daily & Peterson, 2017); on the other hand, predictive analytics is better suited for the early diagnosis of diseases and fraud detection (Cohen et al., 2014; Gerber, 2014). This thesis explores the actualisation of AI in the public sector to answer these questions. Technologies play a vital role in enhancing the capabilities of public institutions, which can result in efficient public service delivery, public engagement, co-production, and public sector innovation (Pang et al., 2014). However, the adoption of advanced technologies can be primarily determined by the business models of public agencies (Pang et al., 2014). The following section presents the concept of the business model and its innovation in the public sector.

2.3.1 Business Model Innovation

The business model concept emerged in the mid-1990s with the advent of the internet (Zott et al., 2011). The business model (BM) concept is defined as a statement (Stewart & Zhao, 2000), a representation (Morris et al., 2005), and a conceptual tool (Al-Debei et al., 2008a; Osterwalder et al., 2005). Al-Debei et al. (2008a) defined a business model as

> an abstract representation of an organisation, be it conceptual, textual, and/or graphical, of all core interrelated architectural, co-operational, and financial arrangements designed and developed by an organisation presently and in the future, as well all core products and/or services the organisation offers or will offer, based on these arrangements that are needed to achieve its strategic goals and objectives. (Al-Debei et al., 2008a, p. 8)

The BM, when explicitly articulated, helps in defining appropriate technology processes, for example, suitable information systems in alignment with strategic goals (Panagiotopoulos et al., 2012).

The BM of an organisation outlines the (1) value proposition (e.g., what value will be created for users by an offering based on new technology), (2) revenue generation model (e.g., identification of such users who will use the technology), (3) structuring of the value chain to highlight the primary and secondary support operations, (4) estimation of expected costs and profits, (5) positioning of vendors and suppliers, and (6) plan to sustain competitiveness (e.g., preparing for the adoption of emerging technologies) (Chesbrough, 2010).

The BM framework suggests that organisations can have one of six types of BMs, ranging from low or none to the highest level of adaptive BMs (Chesbrough, 2007). The six types are (1) no differentiation of BM (i.e., an unarticulated model of business), (2) slight differentiation of BM (i.e., the BM is articulated but still somewhat vague), (3) the model is developed for some segments of the business, (4) the model depicts only the external roadmap (i.e., identification of suppliers and customers but internal roadmaps are not well articulated), (5) BM is aligned with the innovation process (i.e., the technological innovation results in re-defining the BM), and (6) the model is highly adaptive where suppliers and customers are perceived as a business partner (Chesbrough, 2007). These six BM frameworks suggest sequences from essential and less valuable to advanced models.

Technology adoption requires the renovation of the existing business model. For example, Xerox Corporation's BM renovation has been a widely studied case. Xerox faced the high costs of a new electrophotography technology that used dry chemicals for printing. To increase productivity and reduce costs, Xerox changed its BM by leasing the equipment to customers and charging them for every extra copy, over 2,000 copies per month. This model renovation made the customers partners in value creation and resulted in a compound annual growth rate (Chesbrough, 2002). The music industry also witnessed the failure of the traditional BM (releasing cassettes and CDs) due to the launch of online music websites and apps, such as iTunes and SoundCloud. To adapt to this technological revolution, the English rock band, Radiohead, released its album, In Rainbows, on the website with the ‘pay-what-you-want’ model. With this BM, listeners can pay for the songs they want to download. This model helped Radiohead save the costs of hiring a publishing studio by self-releasing the album (Chesbrough, 2010).

2.3.2 Business Models of the Public Sector

In the e-commerce literature, various BM taxonomies have been available for the private sector (e.g., Afuah & Tucci, 2000; Mahadevan, 2000). There had been no established theoretical base for BM research in e-government when Janssen and Kuk (2009) established the first e-government BM framework by drawing on resource-based views, dynamic capabilities, and coordination theories. Their framework suggested that value creation in an e-government business model is subject to various issues, such as coordination between managerial and organisational structures, a collaboration between public agencies, and dynamic capabilities to design, develop and implement new IT knowledge and expertise. This framework also highlights that e-government BMs are abstract and vague, and that more research is needed to refine the value creation process in the government sector.

BMs in the public sector define the product and service offerings, internal working, and external collaborations, and they involve various areas, from delivering services to engaging in public policy (Panagiotopoulos et al., 2012). Public sector BMs are of greater interest due to the change in government interactions with citizens, primarily due to the inculcation of contemporary technologies in the public sector.

The use of business models in the public sector helps identify multi-actors and their interactions for public value creation (Li et al., 2016). Panagiotopoulos et al. (2012) adapted a traditional business model template for public engagement. The traditional pillars of BM, value proposition, value finance, value architecture, and value network (Al-Debei et al., 2008b) were modified for the online petitioning system implemented in the UK’s local authority. In the value proposition, intended benefits were identified as greater geographical reach, political awareness, and engagement of young citizens in e-petitioning. Similarly, communication channels between citizens and politicians were suggested for the value network. Value architecture emphasises technological and structural competencies. The last dimension of BM, value finance, informed technology investments and their impact on three other dimensions. The study's findings suggested that it is not merely the technology that determines success; the BM in which technology is configured is more important than the technology itself. It further identified future research direction by broadening citizen participation to more extendable frameworks on a broader level.

Another study by Micheli et al. (2012) designed a business model for public agencies that focused on commercialising partnerships between public agencies and private firms. Two cases from the U.K. public sector were used in the study and findings indicated that two different commercialisation models were required for technology adoption in two different public sector agencies. They also found that adoption of agency-specific BM facilitates the technology-enabled innovation in public agencies (Micheli et al., 2012). By integrating the technology adoption process with innovation in the business model, public sector agencies can increase value in service delivery (Feller et al., 2011).

In another study, Janssen et al. (2008) developed and applied web-based e-government BM. Based on a survey of 59 e-government websites, eight BMs were found in their taxonomy. However, the elements identified as logic for creating these web-based BMs (1) were derived from the mission of the public organisation, (2) considered the use of the internet to deliver public services, (3) included both products and services, (4) linked the agency's strategy with information system in use, and (5) were independent of temporary technology (adaptive with a technology change). Hence, the need to conduct in-depth case studies with a variety of e-government BMs was raised in this study.

The existing literature on BMs of public agencies has focused on one or more dimensions of BMs, such as value creation or value networks (Janssen & Kuk, 2009; Walravens, 2012), or these have been limited to exploring the role of one or more stakeholders, for example, BMs that solely define the private sector as a business partner (Micheli et al., 2012) or public engagement (Panagiotopoulos et al., 2012). However, little evidence has been found for BMs in public agencies that consider all dimensions of BMs and involve all actors in the process.

As a value-creation and capture tool, the business model can play a significant role in maximizing the value of AI-driven initiatives in public agencies. Therefore, this thesis emphasised the structural reforms in the business models of public agencies to deploy AI in public agencies to create and maximize public value.

2.4 Summary of Chapter

This chapter presented the existing knowledge on AI affordances for the public sector and highlighted the gaps. There are three major sections covered in this chapter. The first section summarizes technology management in the public sector. It highlights the digital evolution of the public sector and how public agencies have transformed from the mere automation of tasks to e-government and are now on the verge of using intelligent agents. This section also extends details on the multifaceted definition of AI and explains the definition that this thesis follows. The section also highlights the research gap in exploring AI's affordances for the public sector. The second section proposes affordance theory that is used in the thesis. The second section presents variants in affordance theory and discusses how the ecological context can be adapted in a public sector setting. It also extends details on why affordance theory is suitable for this these. The third and final section focuses on the actualisation of AI for the public sector. This section highlights the need to renovate the business models of public agencies to deploy AI systems. It summarizes and synthesizes the literature on business model innovation in the public sector.

Chapter 3: Study 1 - AI Policy Analysis

3.1 Foreword to Study 1

Study 1 introduces the dataset, procedure, analysis, and results of 34 national AI plans of countries undertaken to address the first research question (RQ 1) What is the AI affordance perception across the nations? This study outlines the significance of AI as part of a national agenda highlighted by the growing number of countries crafting national, strategic AI plans (OPSI, 2020). These plans offered an understanding of a nation's agenda in harnessing AI and the constellation of related technologies. Also, they could provide insights into how each nation considered various public policies and economic issues that environ AI technologies. This study identified each country's approach toward AI through these national strategic plans. The main findings of the study indicated six common themes among all plans: 1) AI implementation in the public sector; 2) AI implementation in industry; 3) data component of AI systems; 4) algorithms; 5) capacity development for AI; and 6) AI governance. The study contributes to policy analysis and strategic planning domains in the public sector. The study also identifies a valuable source of data for further analysis. For practical significance, this study provides a comparative assessment of plans that can be used to guide further strategic planning efforts.

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3.2 Statement of Contribution of Co-Authors

The authors listed below have certified that:

1. they meet the criteria for authorship and that they have participated in the conception, execution, or interpretation, of at least that part of the publication in their field of expertise;
2. they take public responsibility for their part of the publication, except for the responsible author who accepts overall responsibility for the publication;
3. there are no other authors of the publication according to these criteria;
4. potential conflicts of interest have been disclosed to (a) granting bodies, (b) the editor or publisher of journals or other publications, and (c) the head of the responsible academic unit, and
5. they agree to the use of the publication in the student's thesis and its publication on the QUT's ePrints site consistent with any limitations set by publisher requirements.

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3.3 Abstract

Nations have recognised the transformational potential of artificial intelligence (AI). Advances in AI will impact all facets of society. A spate of recently released national strategic AI plans provides valuable insights into how nations are considering their future trajectories. These *strategic* plans offer a rich source of evidence to understand national-level strategic actions, both proactive and reactive, in the face of rapid technological innovation. Based on a comprehensive content analysis of thirty-four national strategic plans, this article reports on 1) opportunities for AI to modernise the public sector and enhance industry competitiveness, 2) the role of the public sector in ensuring that the two most critical elements of AI systems, data and algorithms, are managed responsibly, 3) the role of the public sector in the governance of AI systems, and 4) how nations plan to invest in capacity development initiatives to strengthen their AI capabilities.

3.4 Introduction

Advances in artificial intelligence (AI) have attracted the interest of public sector agencies across the globe (Yeung, 2020). AI systems are being deployed across the public sector (Agarwal, 2018; Desouza, 2018) and are modernizing the delivery of public services (Sun and Medaglia, 2019). AI solutions can reduce the administrative burden in the public sector by automating routine work (Pencheva et al., 2018). In addition, these systems can serve as interfaces between agencies and citizens, thereby promoting higher-quality service delivery (Sousa et al., 2019). Besides efficient and effective public services, the adoption of AI technologies in the public sector can foster innovation in a number of ways that were not feasible previously, such as the use of data from social media platforms to inform the design and evaluation of public policies (Berryhill et al., 2019).

It is anticipated that the AI revolution will bring about significant disruptions to various socio-economic elements (Berryhill et al., 2019). AI and the rise of automation will impact the future of work and employment (Makridakis, 2017). On one hand, labour-intensive work will be automated (Helbing, 2015; Schwab, 2015), while on the other hand, there might be a rise in new jobs (Wilson et al., 2017). However, it is not clear if the loss of jobs will be compensated for by the increase in new jobs (Bessen, 2018). The deployment of AI has also raised ethical considerations (Jobin et al., 2019).

For instance, various facial recognition tools used by law enforcement agencies have recently been scrutinised for their inaccuracy and their propensity to be biased towards people of colour and minorities (Allyn, 2020). The design of AI systems, especially the level of transparency and auditability of learning algorithms, remains an ongoing concern (Raji et al., 2020). AI-enabled systems can also be weaponised to disrupt public agencies and various processes (e.g., political campaigns and elections) in democratic societies (Desouza, Ahmad, et al., 2020).

Given the significant disruption that is expected due to advances in AI, it is not surprising that nations are now contemplating the practicalities of current and future developments in AI, the impacts of AI-related affordances, and how to address an emerging set of technical, societal, and public policy conundrums that come with AI deployment in a society. The significance of AI as part of a national agenda is highlighted by the growing number of countries crafting national strategic AI plans (OPSI, 2020). These plans provide insights into a nation's agenda in terms of harnessing AI and the constellation of related technologies. In addition, they provide insights into how each nation considers various public policies and economic issues that environ AI technologies. Finally, these strategic plans outline how each nation will coordinate its investment and implementation efforts both within and beyond the public sector to leverage AI for the public good (Fatima et al., 2020a)

While the private sector has made substantial progress in embracing AI and crafting digital transformation strategies (Marr & Ward, 2019; A. Moore, 2019), these practices cannot readily be imported to the public sector. Deploying technologies in the public sector requires greater attention to how public value is maximised (Benington & Moore, 2010), which is a more complex undertaking when compared to maximizing shareholder value. In addition, designing public policies on emerging technologies requires one to navigate a myriad of social, political, and economic considerations while simultaneously ensuring that all sectors and segments of society are accounted for (Morçöl, 2013). Finally, the public sector has a greater requirement to engage citizens in the process of designing public policies and innovations that impact the future of public services (Voorberg et al., 2015).

Given that we are in the early days of witnessing the materialisation of AI affordances in the public sector (Berryhill et al., 2019), research is needed to understand how the trajectory of AI in society might be shaped by national-level strategies and public policies. Toward this end, we gathered and performed a comprehensive analysis of 34 national strategic AI plans. Our objectives were threefold:

1. To capture how each country perceives the role that AI could play in the public and private sectors
2. To understand how each country plans to deal with key technical elements of AI systems, such as data and algorithms
3. To determine how each country plans to develop its AI capacity and address governance challenges that arise from AI systems

3.5 Background

Long-range planning and the crafting of strategic plans are important undertakings in the public sector (Bryson, 1988). Long-range plans offer insights into governments' social and economic development initiatives for a period of five years or more (Wu et al., 2019). The planning process allows agencies to engage input from a diverse set of stakeholders, both inside and outside the public sector (Bryson et al., 2002; Taylor, 1984), and this process generates debates to determine choices, specify future moves, and analyze alternative strategies (Nutt, 1989). The plan itself sets out the vision and ambitions along with key priority areas and the rationale behind these choices (Moxley, 2004).

Long-range planning is helpful when it comes to tackling “wicked problems”: those problems that require redefinition and resolution in different ways over time (Camillus, 2008) and whose solutions are not easily determined (Camillus, 2008; Coyne, 2005). However, fundamental distinctions exist between strategic planning in the public and private sectors that makes tackling wicked problems more complex in the public sector. Unlike the private sector, the public sector is influenced by political reforms and public expectations, and cannot choose to focus on only one set of customers (Ring & Perry, 1985). The multifaceted base of stakeholders not only complicates the process of formulating strategy but also influences the assessment criteria of the plan from the viewpoints of multiple stakeholders (Ramamurti, 1987). While there is a rich literature on strategic planning and the use of strategic plans in the public sector (Barzelay & Campbell, 2003; G. Boyne & Gould-Williams, 2003;

Poister, 2010; Poister & Streib, 2005), limited attention has been paid to strategic plans that focus on information technologies (Yang and Melitski, 2007).

Governments can use policy instruments to achieve various strategic objectives (Borrás & Edquist, 2013). Common types of policy instruments include economic incentives, regulatory controls, and tax levies. The selection of policy instruments, also called “policy mix,” is the operationalisation of the strategic plan into tangible objectives and sets of actions oriented to achieving the overall vision (Borrás & Edquist, 2013). This is the method by which strategic plans move from merely aspirational to practical. Therefore, we intended to explore various policy instruments that nations deem critical for developing their capacity in AI and ensuring that AI is used to advance the public good. Ideally, a strategic plan should outline how a nation visualises the AI opportunity space (including how it relates to a nation’s strengths and weaknesses), which should inform capacity-building initiatives, including investment strategies that target various sectors and industries and the need for regulatory oversight and governance protocols to address the risks posed by AI (World Economic Forum, 2019). As such, strategic plans in the public sector provide a valuable roadmap for understanding both the priorities of the country and the strategy for achieving those priorities. While not perfect, these plans can reflect the prevailing beliefs of a country and how it wants to approach advanced technologies like AI.

3.6 Methodology

3.6.1 Dataset

We built a dataset of national strategic AI plans that existed as of January 31, 2020. The Observatory of Public Sector Innovation (OPSI) (OPSI, 2020) listed 50 nations that have developed or were in the process of developing national AI strategies. We excluded countries that were still in the process of developing their strategic plans. We made the decision to include only published plans based on the belief that in-process plans had not been as thoroughly vetted and agreed upon as those that have been published. To ensure that we did not miss the plans of any countries, we conducted an exhaustive search for plans from other nations. We used search terms such as “National AI,” “AI Strategy,” and “Artificial Intelligence” + “Strategy,” along with the names of countries not on the OPSI list. This effort resulted in finding one more country, Qatar. Upon inspection of each collected plan, we found that for one country, the Netherlands, the plan was not in English. We were able to secure a summary report of their plan in English, and we used that for our data analysis. Hence, our dataset covers 34 nations spanning over 1700 pages (see Appendix A). Two countries released their AI plans in 2016, 5 countries in 2017, 10 countries in 2018, and the maximum number of plans, 16, were released in 2019. For 2020, we explored only up to the 31st of January and found one country, Norway. Most plans are lengthy, ranging 5 pages and up to a maximum of 183 pages.

3.6.2 Research Strategy

Qualitative research is an appropriate method to explore novel phenomena (Yin, 2011). Given the novelty of national-level strategic AI plans, it is appropriate to use a qualitative approach. We undertook a content analysis of the published strategic plans (Cornut et al., 2012). Content analysis is a descriptive and predictive method for analyzing the characteristics of a message (Hsieh & Shannon, 2005; Naccarato & Neuendorf, 1998) and follows a systematic process to extract meaning from data sources through the iterative development of emergent themes (Schreier, 2014; Weber, 1990). It enables the identification of meaning by examining patterns across a range of artefacts. While content analysis begins with enumerating themes of interest and counting the frequency of their occurrence across the dataset, *"*[It] *is more than a counting game; it is concerned with meanings, intentions, consequences, and context. To describe the occurrences of words, phrases, or sentences without considering the contextual environment of the data is inappropriate and inadequate. The analyst must be cognizant of the context and must justify the findings in terms of the context or environment that produced the data. The goal of content analysis is to enhance the inferential quality of the results by relating the categories to the context or environment that produced the data"* (Downe-Wamboldt, 1992, p. 314). Content analysis has been used in research spanning the fields of public administration (Mazzara et al., 2010) , information systems (Gottschalk, 2001) and healthcare (Lega et al., 2013).

We used an inductive and iterative strategy to develop our coding scheme (La Pelle, 2004). To code a chunk of text, we followed Dey's (1993) guidance, which suggests different stages of data coding. During the initial stages, the process is dynamic. However, as researchers move forward in coding, codes become more precise and the decision to code a text in a category becomes clearer. An initial set of codes was generated by manually coding five strategic plans. Next, we used NVivo data analysis software to continue building our list of codes and themes. To ensure the reliability of coding, we randomly selected 10 plans to be coded by two researchers and found that the inter-rater reliability was above 90% (among 20 phrases, 18 were coded in the same concepts by both researchers), which is the acceptance criterion for content analysis (McAlister et al., 2017; Miles & Huberman, 1994). In our initial analysis, we coded all concepts into 122 different codes and then grouped the 122 codes based on similarities. The main concepts are referred to as "themes" and subsidiary concepts as "codes." Finally, we have a set of 6 themes and 37 codes (see Table 3.1).

Table 3.1 *Themes and Codes*

Themes	**Codes**
Public sector functions	1. Healthcare 2. Transportation 3. Education 4. Environment and Natural Resources 5. Energy and Utilities 6. Information and Communication Technologies 7. Public Safety 8. Defence and National Security 9. Courts and the Judiciary 10. Revenue and Tax 11. Immigration, Customs, and Border Protection
Industries	1. Healthcare 2. Agriculture 3. Information Technology 4. Manufacturing 5. Energy and Natural Resources 6. Financial 7. Defence 8. Tourism
Data	1. Data Exchange 2. Data Regulations 3. Privacy 4. Security
Algorithms	1. Explainability 2. Ethics 3. Bias 4. Trust
Capacity development	1. Education 2. Research and Development 3. Public Policy-Driven Innovations 4. Financing
Governance	1. Regulations 2. Risks 3. Social and Economic Inequality 4. Security 5. Intellectual Property Rights Protection 6. Interoperability

3.7 Results

We started by understanding the motivation that inspired different countries to develop their national AI plans. Most plans discussed the major motivation for embarking on AI, identified its enablers, and identified the beneficiaries of the effort and high-level targets of infusion. Most of the plans were aspirational and touched on lofty goals and ideals. Malta's plan was typical in this regard, noting, *"We plan to gradually infuse AI into education, healthcare, and a range of public services to deliver better services to Malta's citizens and businesses, enhance economic and social well-being, and drive operational excellence across the public administration."* (Malta AI Plan, 2019, p. 2). In deconstructing the plans (using Malta as an example), the majority touched on the major motivation (e.g., enhancing economic and social wellbeing), identified its goals (improving service delivery), identified the beneficiaries of the effort (citizens and businesses) and high-level targets of infusion (education, healthcare, and other public services).

Some plans called out key issues they must contend with in the context of AI systems in the public sphere. Consider the Czech Republic's plan, which noted, *"We are going to ensure the safety of driverless cars, robots and autonomous weapons, simply wherever man and intelligent machine meet. We are going to build on our past achievements in mobility and transport, military and security research as well as our historical experience. We are going to focus on protecting every person and consumer, their rights and privacy, especially the weakest ones. We are going to prevent discrimination, manipulation and misuse of AI, we are going to set the rules for decision-making of algorithms about people in everyday life."* (Czech Republic AI Plan, 2019, p. 3). This quote highlights that the country is aware of critical algorithmic (e.g., manipulation of AI), data (e.g., privacy), and governance (e.g., regulating autonomous systems) issues, which will need to be accounted for if it is to achieve its aspirations.

Stakeholder involvement played a significant role in the development of plans, but there were significant differences in terms of who the identified stakeholders were. First, some nations created formal forums that engaged stakeholders in designing their AI plans. For example, Belgium's AI plan said, *"We are leaders from academia, start-ups, corporations, technology firms, and public institutions. We are diverse in age, background, political preference, or convictions about AI. All of us believe it is time* *for our country to take up its responsibilities and capture the opportunities of technology and AI"* (Belgium AI Plan, 2019, p. 4). Second, some plans specifically called for the inclusion of the general public as part of the planning process. The Czech Republic, for example, acknowledged the role of public input for its legal and ethical AI framework, saying, *"A public consultation, including an interactive questionnaire, on the basic legal issues associated with the protection of rights to intellectual property items created by AI and the legal certainty, including Ethical recommendations for the development and utilisation of artificial intelligence."* (Czech Republic AI Plan, 2019, p. 34).

The strategic plans were sparse in implementation details. Several plans, however, discuss a mechanism for reviewing implementation progress. For example, the Russian plan outlined, *"On an annual basis, [the AI implementation team should] submit a report to the President of the Russian Federation concerning progress in the implementation of the National Strategy for the Development of Artificial Intelligence over the period extending up to the year 2030."* (Russia AI Plan, 2019, p. 3). China's plan had a bit more detail over what the reporting should look like, saying that the plan should *"Clarify responsibility units and schedule. Develop annual and phased implementation plan. Establish annual assessments, mid-term assessments and other implementations of the monitoring and evaluation mechanism. Adapt to the rapid developments of AI according to the progress of the tasks. The completion of the stage objectives, new trends in technology development. Strengthen the planning and project dynamic adjustment."* (China AI Plan, 2017, p. 28). However, most plans did not contain any information on the actual implementation strategies or tracking mechanisms, and this highlights the largely aspirational nature of the plans. (See appendix B to G for analysis output)

Most plans detailed two aspects a) how national governments should leverage AI to modernise the public sector, and b) how industries and industrial sectors should take advantage of AI affordances to maintain and extend their competitiveness. Some plans went a step further to clarify the specific role that the government should play. Consider the USA's plan, which notes, *"The Federal government should therefore emphasize AI investments in areas of strong societal importance that are not aimed at consumer markets—areas such as AI for public health, urban systems and smart communities, social welfare, criminal justice, environmental sustainability, and* *national security, as well as long-term research that accelerates the production of AI knowledge and technologies"* (USA AI Plan, 2016, p. 7). Here, there is a specific call for the federal government to target its investments in areas that might not be considered by the private sector.

Plans acknowledged the critical role that the private sector will play when it comes to advancing AI to meet national priorities. For example, Finland's plan said, *"Thus far, companies have played the largest role in the development and application of artificial intelligence. It is companies rather than state initiatives that have achieved the most central impacts. Companies will play a particularly important role in applying the benefits of artificial intelligence and in investing in these. Companies also typically have extensive data resources, the utilisation of which is critical to both the development and application of artificial intelligence. while others place industries as of secondary importance."* (Finland AI Plan, 2017, p. 32).

3.7.1 Public Sector Functions

Eleven public sector functions were highlighted in our dataset. The distribution of the coverage of public sector functions was not uniform. China's plan covered the most public sector functions (nine), while plans of three European countries (Austria, Sweden, and Poland) each mentioned only one public function.

3.7.1.1 Healthcare. Twenty-eight countries identified the critical role that AI can play in modernizing public healthcare systems. Plans focused on two aspects. The first was AI's role in increasing the efficiency of healthcare systems. For example, the Czech Republic's plan called for the *"…use of AI as part of providing health services, administration of medicinal products and medical devices and in reimbursement processes, reporting of interventions, predictions of cost development and other data processing, especially within the fulfilment of the National eHealth Strategy of the Czech Republic 2016–2020"* (Czech Republic AI Plan, 2019, p. 24). The second was the role that AI could play in fostering medical innovations. Portugal's plan called out the *"…significant potential for AI to deliver benefits in this sector, such as by discovering new drugs, reducing costs, diagnosing diseases, improving patient care, personal medicine and public health"* (Portugal AI Plan, 2019, p. 31).

3.7.1.2 Transportation. Twenty-five countries referred to the role that AI would play in modernizing public transportation networks. For example, India's plan highlighted that an AI-enabled transport system could provide *"...real time dynamic decisions on traffic flows such as lane monitoring, access to exits, toll pricing, allocating right of way to public transport vehicles, enforcing traffic regulations through smart ticketing etc."* (India AI Plan, 2018, p. 44). Denmark's plan was slightly more modest than the others and discussed, *"*[Using} *Location data in the transport area which can relieve congestion and help urban planning by analysing traffic patterns"* (Denmark AI Plan, 2019, p. 38).

3.7.1.3 Education. AI systems are poised to transform our educational systems by improving the student learning experience, improving teacher–student interactions, and modernizing learning platforms (Timms, 2016a). Fifteen countries recognised the potential of AI in the context of public education systems. Some of these plans focused on how AI will transform students' learning experiences. Italy's plan discussed the role of AI in personalised learning to *"...follow students individually, suggesting content and concepts selected to help them develop their skills, deepen their knowledge, or bridge the gap with their fellow students"* (Italy AI Plan, 2018, p.16), while similarly, India's plan mentioned that *"Assessing time spent by a student on each part / page of the learning material, for example, would allow real-time feedback on student performance to help the teacher appropriately tailor her guidance to the child. This concept can be extended to automatic grading of tests, as well."* (India AI Plan, 2018, p. 37). Plans also noted that AI could help design solutions for common and costly challenges (e.g., low student retention) found in the educational sector. Malta's plan, for example, noted, *"[Embarking on] a pilot project to construct a rich data set and use AI to assist in driving insights and actions to enhance the education system. The initial project will focus on delivering predictive insights to assist in identifying early school-leavers to help educators take preventative actions to drive better outcomes."* (Malta AI Plan, 2019, p. 28).

3.7.1.4 Environment and Natural Resources. Fourteen countries called for the potential of AI to advance a sustainable environment and natural resource management. For example, New Zealand's plan noted that *"AI can help address our environmental concerns by analysing data and providing better detection and environmental management tools. AI can also be used in the redesign of industrial processes to make them more sustainable overall."* (New Zealand AI Plan, 2018, p. 61). Spain's plan is more expansive and noted, *"The impact of external factors on* *these resources can be predicted and measured through intelligent weather and climate prediction systems and intelligent systems for early response to natural disasters. In the energy sector, AI contributes to efficiency through multi-agent systems in intelligent energy distribution grids and applications or agent-based modeling for energy sustainability."* (Spain AI Plan, 2019, p. 33).

3.7.1.5 Energy and Utilities. Thirteen plans acknowledged the potential of AI to transform the energy sector. Most plans focused on how AI can increase the efficiency of current energy networks and can lower a nation's dependency on foreign resources. Lithuania's plan noted, *"The energy sector should utilize AI systems to create more efficient methods for delivering power. With a more efficient approach to power distribution, Lithuania can increase sustainability and become less dependent on foreign sources of energy."* (Lithuania AI Plan, 2019, p. 15).

Nations recognised the need to plan for greater pressure on the current energy networks due to increased demand for energy and the need to increase reliance on these networks to be able to support innovations powered by AI. As noted in Malta's plan, "*Demand is also expected to increase, along with the number of electric vehicles on the road, with more viable battery technology and greater roll-out of electric vehicle charging points. These shifts will require new capacity from the grid and improvements in the system resilience of Malta's energy supply"* (Malta AI Plan, 2019, p. 32).

3.7.1.6 Information and Communication Technologies. Thirteen plans explicitly recognised the need to invest in and modernise digital infrastructure to support AI development. China, for example, noted its intention to "*Speed up the layout of real-time collaboration with AI 5G. Enhance the technology research and development and application. Construct space-oriented collaborative AI of high-precision navigation and positioning network. Strengthen the core of intelligent sensor network technology research and key facilities. Develop and support of intelligent industrial Internet, for unmanned car networking, research intelligence Network security architecture."* (China AI Plan, 2017, p. 22). Similarly, Germany's plan called for investment in 5G infrastructure: *"it is essential for the network infrastructure (e.g. the 5G standard) to be further developed so that the potential of AI for this sector can be harnessed."* (Germany AI Plan, 2018, p. 17).

3.7.1.7 Public Safety. Eleven countries recognised the critical role that AI can play when it comes to bolstering public safety. Plans discussed how AI can enable law enforcement operations both in the field (e.g., the use of robots) and in back-office functions (e.g., to speed up administrative processes through automation).

For example, Germany's plan said, *"Autonomous and semi-autonomous systems can be used to support civil security officers, ease their burden and eliminate the need for them to be present in dangerous situations. There are plans for robots to be used especially in critical circumstances arising in an inhospitable environment, for instance when there has been a calamity in a chemical factory or when the structure of buildings has to be assessed in the wake of an earthquake."* (Germany AI Plan, 2018, p. 17).

India's plan showed interest for city design as" Smart cities aim to address the issues of increase in crime and increased risk of urban emergencies through improved city design and surveillance analytics (India AI Plan, 2018, p.39)

3.7.1.8 Defence and National Security. There is significant activity when it comes to research and development and the current deployment of AI across the defence and national security environment. For example, R&D efforts on autonomous weapon systems have already been tested in the context of drones that can target and hit enemy radar installations (Simonite, 2019). AI-enabled systems are also used extensively by national security agencies for intelligence, surveillance, reconnaissance, logistics, and cybersecurity operations (Hoadley, 2019). However, only 9 plans mention national defence and security. USA's plan said that *"Machine learning agents can process large amounts of intelligence data and identify relevant patterns-of-life from adversaries with rapidly changing tactics. These agents can also provide protection to critical infrastructure and major economic sectors that are vulnerable to attack. Digital defense systems can significantly reduce battlefield risks and casualties."* (USA AI Plan, 2016, p. 11). Germany's plan noted that *"The use of AI-based technologies and systems will have implications for the armed forces and is therefore an important issue to be taken into account for the future of the Bundeswehr. As in other fields of application, the Federal Government will undertake a comprehensive analysis of the benefits and risks involved."* (Germany AI Plan 2018, p. 31)

3.7.1.9 Courts and the Judiciary. Five countries noted that AI systems can streamline the litigation process and improve the performance of courts through automation. The Czech Republic took a broad view of AI in the judiciary and said, *"Introduction of AI elements in the judiciary, such as the sounding of all recording halls, the use of spoken word transcripts in selected agendas, and the involvement of artificial intelligence elements in the justice anonymizer"* (Czech Republic AI Plan, 2019, p. 35). Similarly, Italy called for *"...reduction of civil litigation through easier access to legislation and jurisprudence; digitisation of documents and understanding of the text and information present"* (Italy AI Plan, 2018, p. 22).

3.7.1.10 Revenue and Tax. Given the significant potential for AI systems to add value to the revenue and tax agencies of the public sector, we were surprised to find that only 4 strategic plans called out opportunities in this space. Mexico's plan noted that its Tax Administration Service *"was trialing AI algorithms to detect companies that are conducting fraudulent operations, by identifying pattern disruptions in data analyzed using R Studio, Python Language, and DBs in-memory Redis. Within three months of a six-month pilot scheme, 1200 fraudulent companies were detected and 3500 fraudulent transactions identified"* (Mexico AI Plan, 2018 p. 23). Denmark's plan called for a *"more efficient tax system and better possibilities to combat fraud in VAT, tax and social benefits"* (Denmark AI Plan, 2019, P. 11).

3.7.1.11 Immigration, Customs, and Border Protection. AI systems support effective border control and immigration services (Ajana, 2015). Finland and Singapore called for the use of AI to modernise immigration and border control operations. Finland's plan is ambitious and noted, "One such example has already been introduced at the Finnish Immigration Service, where phone calls were answered in all the required languages. Artificial intelligence can be used to create a new type of servant for every public organisation. These servants together form a robot network where customers are a uniform unending chain. When a customer's service need arrives for any robot to process, it can be assessed and optimised in real-time cooperation with robots from other organisations. A plan is being drawn up for a national customer service robot network, the Aurora assistant. The Finnish Immigration Service's solution for immigrants will be used as the starting point for the plan" (Finland AI Plan, 2017, p. 54). Singapore's plan noted, "We will also study how to redesign our immigration clearance process to enable all travelers to enjoy secure and seamless immigration clearance experience via automated clearance facilities" (Singapore AI Plan, 2019, p. 36).

3.7.2 Industries

Strategic AI plans detailed how governments have envisioned the transformation of major industries and sectors of the economy. For example, the Lithuanian plan said, *"Manufacturing is the largest sector of the Lithuanian economy, generating 20.4% of the country's GDP. The biggest challenges faced by the Lithuanian manufacturing sector are the low levels of labor productivity. Artificial intelligence systems can mitigate these challenges by automating routine tasks. Together with intelligent robotics systems, the manufacturing sector looks to reap some of the biggest benefits from AI"* (Lithuania AI Plan, p. 14, 2019). The list of industries expected to contribute to, or benefit from, a national AI strategy is impressive and, in our analysis, includes virtually every major industry in the respective countries. In total, we found eight industries highlighted consistently across the collection of strategic AI plans.

3.7.2.1 Healthcare. Healthcare was the most-cited industry and appeared in 20 plans. For example, Luxembourg's plan noted, *"The healthcare industry will experience boosted efficiency, real-time analysis, predictability and quality care. Personalized medicine is a major priority for Luxembourg"* (Luxembourg AI Plan, 2019, p. 11). Germany showed a more opportunistic approach and said, *"We will make use of the opportunities AI offers for the healthcare sector and support the use of data from distributed sources – always in conformity with data protection law and taking account of patients' protected interests"* (Germany AI Plan, 2018, p. 18).

3.7.2.2 Agriculture. Agriculture was the second most-cited industry and appeared in 16 plans. In countries with a large agriculture sector, AI was a tool to help increase efficiency in operations. As an example, consider India's plan, which notes, *"Increasing efficiency of farm mechanisation: Image classification tools combined with remote and local sensed data can bring a revolutionary change in utilisation and efficiency of farm machinery, in areas of weed removal, early disease identification, produce harvesting and grading. Horticultural practices require a lot of monitoring at all levels of plant growth and AI tools provide round the clock monitoring of these high value products"* (India AI Plan, 2018, p. 33). Similarly, the Australian plan indicated the use of agricultural robots, *"An on-farm agricultural robot Agbot II developed by the Queensland University of Technology could save Australia's farm* *sector AU$1.3 billion per year by automating weed removal and improving agricultural productivity"* (Australia AI Plan, 2019, p. v).

3.7.2.3 Information Technology. Most plans rightfully acknowledge the critical role that the IT sector will play in terms of developing their capacity for AI. Sixteen plans discussed the role of AI in the information technology industry. For example, the New Zealand plan said, *"The tech sector has among the greatest potential for economic growth from AI. Integrating AI into legacy information and communications systems is expected to quickly deliver significant cost, time and process related savings. High growth areas within this industry are cloud, network and systems security (including defining enterprise wide cloud security strategies)"* (New Zealand AI Plan, 2018, p. 46). UK's plan referred to encouraging IT sector by saying, ,[government] *"should produce clear guidance on how the apprenticeship levy can be best deployed for use in the technology sector"* (UK AI Plan, 2018, p. 58)

3.7.2.4 Manufacturing. The manufacturing sector was highlighted in 14 plans. For example, New Zealand's plan noted, "As manufacturing is expected to be one of the major adopters of the Internet of Things (IoT) this will be a powerful catalyst for AI use. Based on the proliferation of IoT devices and the networks and terabytes of data they generate, it is predicted that AI will contribute to a strong growth in profitability for the manufacturing sector" (New Zealand AI Plan, 2018, p. 46). Some plans recognised that the manufacturing sector will undergo disruption due to the changing economics of production and labour costs. Finland's plan noted, "that the competitiveness of the manufacturing industry may also improve in countries with high cost structures, such as Finland. Factories will become agile production facilities that can be converted for various needs and places where people and automation work together flexibly" (Finland AI Plan, 2017, p. 23).

3.7.2.5 Energy and Natural Resources. The energy industry featured prominently in plans and was noted in 14 plans. Spain's plan discussed AI's role in sustainable development of the energy sector and said, *"In the energy sector, AI contributes to efficiency through multi -agent systems in intelligent energy distribution grids and applications or agent-based modeling for energy sustainability"* (Spain AI Plan, 2019, p. 33). Lithuania's plan took a broad view and said, *"The energy sector should utilize AI systems to create more efficient methods for delivering power. With a more efficient approach to power distribution, Lithuania can increase sustainability* *and become less dependent on foreign sources of energy."* (Lithuania AI Plan, 2019, p. 15)

3.7.2.6 Financial. Eight countries highlighted the financial industry in their plans. Spain's plan referred to advanced financial technologies by saying, *"Mention should be made of the financial industry's use of these technological advances by adapting Distributed Ledger Technologies as the blockchain"* (Spain AI Plan, 2019, p. 12). There was also mention of how the public sector should work with the financial industry to minimise risks associated with the use of AI in the sector. For example, Singapore's plan said, "*Artificial Intelligence and Data Analytics (AIDA) driven decisions, without proper governance and accountability structures, may potentially erode the fabric of financial services. For these reasons, the Monetary Authority of Singapore (MAS) worked with the financial industry to co-create a set of principles to guide the responsible use of AIDA in financial services"* (Singapore AI plan, 2019, p. 67).

3.7.2.7 Defence Six. countries mentioned the defence industry in their strategic AI plans. The defence sector was seen as a critical collaborator to advance the deployment of AI-enabled solutions in all facets of national security operations. China's plan noted, *"Promote the two-way conversion application of military and civilian scientific and technological achievements, build and share military and civilian innovation resources, form the new pattern of military and civilian integration of all elements, multi-field, high efficiency"* (China AI Plan, 2017, p. 4). USA's plan said "*Computing technology is critical to every aspect of modern life, but the information systems we use daily lack the general, flexible abilities of human cognition. In the Personalized Assistant that Learns (PAL) program, DARPA set about to create cognitive assistants that can learn from experience, reason, and be told what to do via a speech interface. DARPA envisioned PAL technologies making information systems more efficient and effective for users. DARPA and the PAL performers worked with military operators to apply PAL technologies to problems of command and control, and PAL procedure learning technology was integrated in the U.S. Army's Command Post of the Future version Battle Command 10 (see figure) and used around the world* (USA AI Plan, 2016, p. 25)

3.7.2.8 Tourism. Six plans made specific mention of the tourism industry. For example, Malta's plan said that "AI models are being applied to big data to discover industry trends and sentiment (i.e. what tourists like and dislike) at scale, provide recommendations on places to visit and book, and enable hotels and vacation rental owners to deploy automated pricing solutions based on supply and demand" (Malta AI Plan, 2019, p. 12). New Zealand's plan anticipates the potential of AI in tourism as, "Also, the ability to intelligently analyse growing New Zealand tourism activity datasets will provide opportunities to design more personalised visitor experiences" (New Zealand AI Plan, 2018, p. 46).

3.7.3 Data

The critical ingredient for AI systems is data. The data helps inform the development of algorithms and the output of AI systems. AI systems thrive on having access to large datasets that come in various forms (images, videos, text, etc.) and from multiple sources (e.g., social media platforms, corporate information systems, IoT sensors, etc.). National-level interest in the economics of building and managing large-scale data repositories has increased in recent times (Desouza & Jacob, 2017). The performance of AI systems is often a function of the data used to train the algorithms. In recent times, we have seen cases where AI systems have caused grave harm, e.g., incorrectly sentencing people to jail (Hao, 2019a) due to a lack of care in data management when training the algorithms (Bozdag, 2013; Danks & London, 2017). Clearly, as countries contemplate the role that AI will play in society, it will be important to give due consideration to the data.

3.7.3.1 Data Exchange. Most strategic plans recognised the critical role that the public sector needs to play in terms of fostering the exchange of data between various stakeholders. First, governments need to take a more active role in promoting the sharing of data between themselves and other stakeholders (e.g., citizens, businesses, academia, etc.). Thirty-one plans discussed this issue. For example, in discussing this issue, the Singapore plan noted, *"As the nation's custodian of personal and administrative data, the Government holds a data resource that many companies find valuable. The Government can help drive cross-sectoral data sharing and innovation by curating, cleaning, and providing the private sector with access to Government datasets. The envisaged Public-Private Data Sharing Framework will facilitate the sharing of Government data with non-Government entities (NGEs) and key commercial partners, by defining the scope, type, granularity, and safeguards (people, process, and technical) of Government data that can be shared with the private sector"*

(Singapore AI Plan, 2019, p. 62). India's plan called for a data marketplace: *"The proposed data exchange marketplace will attract data providers and model builders / trainers to build AI products. The process of exchange, with enforced provisions of privacy and anonymisation, brings a market determined value to data and thus forces the existing informal data exchange economy, without any privacy protection, to move towards a formal economy"* (India AI Plan, 2018, p. 79).

Second, plans discussed the need for greater data sharing between various public agencies. Twenty-eight plans recognised the need for the public sector to improve how data is shared between agencies to obtain a more holistic view of various elements (e.g., how citizens interact with various public services) to better provide an integrated and seamless experience. For example, Lithuania's plan said, *"A centralized hub for data administration in the public sector would unify Lithuania's approach to data and promote more involvement from the public sector in the open data ecosystem. The hub will create standards for data literacy that will ensure data is managed correctly"* (Lithuania AI Plan, 2019, p. 20). Similarly, Singapore's plan noted, *"In June 2018, Singapore's Smart Nation and Digital Government Office launched a Government Data Strategy that sets out action plans to manage data as a strategic asset and deepen the Government's use of data by 2023. The GDA is a key thrust of the Government Data Strategy, and aims to enable secure data sharing between Government agencies within 7 working days"* (Singapore AI Plan, 2019, p. 63).

Third, 20 plans discussed the exchange of data between nations. For instance, Denmark's plan focuses on cross-border data sharing and said *"The EU Coordinated Plan on Artificial Intelligence states that more data from public authorities and businesses should be shared and made available across national borders. The first step towards a common European data space is the PSI Directive, which will ensure that all EU Member States make certain spatial data, environmental data, weather data, etc. freely available at the European level"* (Denmark AI Plan, 2019, p. 40). Similarly, Qatar's plan recognised that it could take a leadership role to foster the cross-country sharing of data, *"For most countries including Qatar, developing successful AI applications that can generate export revenue won't be possible without greater data sharing at a global level. There is no such multilateral initiative in the world, hence this is an opportunity for Qatar to take a leadership role"* (Qatar AI Plan, 2019, p. 8).

3.7.3.2 Data Regulations. Attention to the need for regulations to ensure responsible data ownership and use was found in 25 plans. Denmark's plan noted that *"Uncertainty about the rules should not constitute a barrier to using and sharing data as a source of innovation and growth in the Danish business community. Therefore, as part of the Strategy for Denmark's Digital Growth, the government has prepared guidance materials for businesses about the rules for ownership and rights in connection with the use and sharing of data. This will ensure clarity about the rules for businesses and their use of data"* (Denmark AI Plan, 2019, p. 34).

Serbia's plan also said *"Particular attention is paid to this issue and to aligning the Strategy with the Law on Personal Data Protection of 2018, which also complies with the GDPR and European Union regulations in this area. The challenge identified in the regulatory framework refers to the establishment of balance between regulations in the field of personal data protection and leaving room for the development of artificial intelligence and innovations in this field."* (Serbia AI Plan, 2019, p. 8)

3.7.3.3 Privacy. Designing AI systems while preserving the privacy of data is a challenge for governments. The increase in the number of digital interactions between government and stakeholders makes data more vulnerable to privacy violations and security breaches (van Zoonen, 2016; L. Yang et al., 2019). Thirty-one plans discussed data privacy, for example, Qatar's plan emphasises privacy concerns, saying, *"Qatar's Ministry of Transportation and Communication (MoTC) and previously ictQatar (which is now part of MoTC) had issued guidelines for Qatar on privacy and data sharing that are in alignment with Qatar's traditions and ambitions. These would form an excellent starting point to develop a larger and comprehensive set of guidelines for the country"* (Qatar AI Plan, 2019, p. 13). India's plan said, *"The proposed data exchange marketplace will attract data providers and model builders / trainers to build AI products. The process of exchange, with enforced provisions of privacy and anonymisation, brings a market determined value to data and thus forces the existing informal data exchange economy, without any privacy protection, to move towards a formal economy"* (India AI Plan, 2018, p. 79)

3.7.2.4 Security. Thirteen plans specifically referred to the security of data. Germany's plan referred to data security as, "*We want our specific data stock to be used to the benefit of our society, the environment, business, culture and country, and* *for AI-based business models to be developed in Germany and to become new top exports, whilst strictly observing data security"* (Germany AI Plan, 2018, p. 8).

Korea's plan mentioned, "Realize a data-based society equipped with a rational and data-based decision-making system that enables anyone to easily find and secure the data they need to create new value. Transform Korea from a data-poor country into a data-rich one." (Korea AI Plan, 2016, p. 34)

3.7.4 Algorithms

If data is the critical input for AI systems, algorithms are the machinery that enables us to make sense of data, build learning models, and design semi- or fully autonomous systems. Algorithms that drive AI systems continue to be scrutinised because of their lack of transparency and explainability, especially when these systems are deployed in the public sector (Janssen & Kuk, 2016a). Hence, it was surprising to find that most AI plans had little to say on how nations would ensure that the design and deployment of algorithms would be conducted in a manner that minimises harm to the public and contributes positively to enhancing public value. We found four concepts: 1) explainability, 2) ethics, 3) bias, and 4) trust.

3.7.4.1 Explainability. The black-box nature of AI algorithms hinders their explainability due to the complexity and unreadability of choices made during processing (Barton, 2019). Twenty-three plans recognised the need for nations to take active measures to address how to design public policies to address this issue. France's plan said, *"…algorithms has become a very urgent matter and is now actually a separate field of research, which must be supported by public authorities. Three areas in particular require an extra focus: obviously the production of more explicable models, but also the production of more intelligible user interfaces and an understanding of the cognitive mechanisms used to produce a satisfactory explanation"* (France AI Plan, 2018, p.15).

Denmark's plan differentiated between transparency and explainability by saying, *"Explainability is not the same as full transparency of algorithms, as there are business interests in the private sector, for example. However, the public authorities have a special responsibility to ensure openness and transparency in the use of algorithms"* (Denmark AI Plan, 2019, p. 28). Based on our analysis of plans, it is quite concerning that more attention has not been given to the details on why the public sector needs to take the lead in ensuring that algorithms are both transparent and can be interrogated as to their functioning.

3.7.4.2 Ethics. Ethical quandaries are plentiful when it comes to the application of algorithms and autonomous systems in society (Mittelstadt et al., 2016b). Eighteen plans called out the need to pay attention to ethical issues as they pertain to AI-enabled systems. Germany's plan noted *"The Federal Government will assess how AI systems can be made transparent, predictable and verifiable so as to effectively prevent distortion, discrimination, manipulation and other forms of improper use, particularly when it comes to using algorithm-based prognosis and decision-making applications"* (Germany AI Plan, 2018, p. 38).

Norway's plan noted, *"Algorithms can be controlled by facilitating access or audit, but it is more appropriate for developers as well as users to build privacy and ethical considerations into systems from the outset. Such a mindset has already been established with regard to privacy"* (Norway AI Plan, 2020, p. 60). Resolving how to design algorithms that take a value-sensitive approach to their design and ensure that ethical considerations are accounted for remains a critical challenge. The public sector should take charge on this front because the private sector has not stepped up to lead regarding this issue.

3.7.4.3 Bias. Underrepresentation of a social group in training data or feature selection in algorithmic design leads to a biased outcome that causes social discrimination (Veale et al., 2018). To date, we have seen several instances of algorithms trained with biased data leading to prejudicial outcomes. Eighteen plans made specific mentions of the issue of bias. The United Kingdom said, *"These systems are designed to spot patterns, and if the data is unrepresentative, or the patterns reflect historical patterns of prejudice, then the decisions which they make may be unrepresentative or discriminatory as well"* (UK AI Plan, 2018, p. 41). Italy's plan also considered bias and said, *"However, Artificial Intelligence can also increase inequalities, if the data it feeds on or the algorithms that make it up are affected by discriminatory bias. Therefore, the Public Administration must pay great attention to the development of inclusive, accessible, transparent, not discriminatory and free from bias solutions"* (Italy AI Plan, 2018, p. 9).

3.7.4.4 Trust. Trust in autonomous systems and the outcomes they generate remains a critical concern across all facets of society (Janssen & Kuk, 2016a).

Nineteen plans called out trust as an element that needs to be monitored in the context of AI systems. USA's plan noted, *"To achieve trust, AI system designers need to create accurate, reliable systems with informative, user-friendly interfaces, while the operators must take the time for adequate training to understand system operation and limits of performance"* (USA AI Plan, 2016, p. 28).

Italy identified co-creation as a technique to build people's trust in AI. *"The introduction of AI in people's lives requires the design of processes that facilitate the understanding and acceptance of technologies by the user, not only through the use of experimentation but also through collaboration mechanisms that allow citizens to participate in the design of AI platforms. Thanks to the co-creation approach, as happens in design thinking, users perceive technology as their own and show a greater propensity to use it. Moreover, where issues or problems in its use are found, citizens show a greater propensity to actively participate in their solution"* (Italy AI Plan, 2018, p. 28).

3.7.5 Capacity Development

Nations recognised the significant effort needed to build capacity to be prepared for a world where AI systems are pervasive and ubiquitous. The four broad categories of capacity development are 1) education, 2) research and development, 3) public-policy-driven innovations, and 4) financing.

3.7.5.1 Education. Investing in educational initiatives was the most significant capacity-building initiative. Our analysis revealed four areas of investments: a) higher education, b) primary and secondary education, c) vocational training, and d) lifelong learning. Fourteen plans mention all four areas as part of their capacity development efforts.

Building capacity through investments in higher education was the most common among the four areas and was found in 31 plans. Denmark's plan said, *"New programmes on artificial intelligence are constantly being set up. For example, in 2018 the Technical University of Denmark set up a new BSc programme on artificial intelligence and data. In 2019, the University of Copenhagen will set up a new BSc programme on machine learning and data science"* (Denmark AI Plan, 2019, p. 44). Similarly, Finland's plan noted, *"A Master of Artificial Intelligence further education programme and degree programme are being created. The programme will be* *modular and will be possible to complete while going to work"* (Finland AI Plan, 2017, p. 52).

Twenty-six plans noted the need to invest in AI programs at the primary and secondary school levels to instill interest in STEM (science, technology, engineering, and mathematics) education during the early years of a child's education. Belgium's plan noted, *"Children in our primary and secondary schools should get acquainted with coding, technology, and AI, from an early age. First, we must make STEM more attractive as a field of study, particularly for girls. Next, we need to incorporate algorithmic thinking in the curriculum and incorporate technological skills in the existing courses* (Belgium AI Plan, 2019, p. 12). Italy's plan referred, *"Already today, however, it is important that the school system and the university system enable students for the future in which they will live as adults, therefore developing problem solving and information analysis and synthesis skills, as well as those of formulation of independent opinions, creativity, empathic interaction and refined use of one's sensory and psychomotor capacities, areas in which it will be difficult for machines to compete with human beings"* (Italy AI Plan, 2018, p. 23).

Twenty-four plans discussed the importance of vocational courses to increase access to learning options for computer-science-related skillsets. Germany's plan specifically mentions vocational training and said, *"The draft legislation wants to give employees whose jobs are at risk of becoming lost to technologies, those otherwise affected by structural change, and those wishing to train for a profession for which is labour is scarce, an opportunity to acquire the skills they need. This will also include employees whose jobs will be taken over by artificial intelligence. From 2019, under the Opportunities for Qualifications Act, the Federal Government wants to give workers belonging to the groups described above, and also workers claiming benefits pursuant to the Social Code II in addition to their work, an opportunity to adjust and deepen their professional skills base – irrespective of their previous level of education, age and of the company's size"* (Germany AI Plan, 2018, p. 26).

Denmark's plan described, *"Teknologipagten (Technology Pact) and the future STEM action plan will raise the skills of the workforce, and it is important that more young individuals are encouraged to take digital and technological education programmes focusing on artificial intelligence, for example. In Teknologipagten, the government has set a goal that in 10 years Denmark will have about 10,000 more* *people with higher or vocational qualifications within the so-called STEM disciplines"* (Denmark AI Plan, 2019, p. 45).

Twenty-two plans identified the need to invest in lifelong learning solutions to keep their workforce relevant given the disruptions expected to jobs due to advances in AI. Belgium's plan discusses the value of lifelong learning and said, *"We need to create a momentum that urges all stakeholders, including trade unions, to invest in, and incentivise for, lifelong learning. We can do this, amongst others, by raising awareness on potential job changes. For example, further studies should be conducted on the impact of AI at work and the interaction between technology and people. Moreover, it will prompt a focus on the jobs most at risk in the next few years"* (Belgium AI Plan, 2019, p. 11). Luxembourg's plan referred to, *"Lifelong learning programs will need to be strengthened and specific digital and AI-related training programs will need to be offered to allow firms, employees and the unemployed to successfully adapt to a changing labor market"* (Luxembourg AI Plan, 2019, p. 22).

3.7.5.2 Research and Development. Investing in research and development to advance discoveries in AI featured prominently in strategic AI plans. We identified three distinct R&D initiatives: a) encouraging multisector research collaboration, b) direct research funding, and c) setting up dedicated AI research institutes. Twenty-two plans referred to all three R&D components.

First, 31 plans discussed the importance of multisector research collaboration. For example, *"Establishing the cooperation of scientific research institutions, the business sector and the public sector in the innovative application of artificial intelligence"* (Serbia AI Plan, 2019, p. 34). The Czech Republic's plan echoed, *"Creating specialized AI ecosystems linking research centres to the business community, which will support AI deployment by sector and industry, primarily through dedicated support activities, technical talent training, research, teaching and application area collaboration"* (Czech Republic AI Plan, 2019, p. 24).

Second, 28 plans discussed the importance of the allocation of AI research and development funds by national governments. These funding initiatives took various forms, such as funding for universities to conduct AI research, funding collaborative industry-academia projects, and promoting international AI research forums. For example, Denmark's plan said, *"The Budget also allocates DKK 80 million (EUR 10.7 million) to the Independent Research Fund Denmark to conduct research into digital* *technologies, including artificial intelligence. In the years ahead, the government will continue to prioritize research into digital technologies, such as artificial intelligence"* (Denmark AI Plan, 2019, p. 46). Luxembourg's plan said, *"The Ministry of the Economy has allocated approximately €62M in 2018 for AI-related projects through R&D grants, while granting a total of approximately €27M in 2017 for projects based on this type of technology. The Luxembourg National Research Fund (FNR), for example, has increasingly invested in research projects that cover big data and AI-related topics in fields ranging from Parkinson's disease to autonomous and intelligent systems – approximately €200M over the past five years"* (Luxembourg AI Plan, 2019, p. 6).

Third, 24 plans discussed the importance of setting up AI-dedicated research institutes within the public sector to accelerate AI research. For example, France's plan said, *"In such a context, it is proposed to set up four to six interdisciplinary institutes for Artificial Intelligence (3IA institutes) nationwide, organized into a network: the National Network of Interdisciplinary Institutes for Artificial Intelligence (RN3IA)"* (France AI Plan, 2018, p. 64). Germany's plan also indicated the role of an AI research centre, *"A special role in this will be played by the German Research Center for Artificial Intelligence (DFKI), which is the world's largest research institute dedicated to AI and has earned itself a very strong reputation internationally. Thanks to its excellent implementation strategy, the DFKI has given rise to more than 70 spin-off companies so far, and a large number of patents in various fields of AI"* (Germany AI Plan, 2018, p. 13).

3.7.5.3 Public Policy-Driven Innovations. Strategic plans outlined four types of policy innovations that were needed to bolster a nation's AI capacity: a) pilot projects, b) attracting international AI experts, c) procurement, and d) business model innovation. Given that we are in the early days of designing and deploying AI systems, 21 plans recognised the need to support responsible experimentation by setting up pilot projects. For example, Italy's plan mentioned, *"As with many other technologies, it is advisable to test the AI on a small scale before applying it at full capacity in its activities. Developing a pilot program allows those who decide to implement AI solutions to become familiar with the technology and to correct any errors during development, thus allowing the service itself to improve"* (Italy AI Plan, 2018, p. 38). Norway's plan said, *"The Government wants public sector organisations to facilitate* *experimenting with artificial intelligence to gain knowledge about and experience in the technology. Trial projects or pilots in AI will provide valuable experience that can be used when evaluating large-scale projects and can enhance understanding of the technology at all levels in the organisation"* (Norway AI Plan, 2020, p. 54).

As the battle to recruit, develop, and retain AI talent intensifies, governments have a critical role to play when it comes to positioning the nation as a destination for AI expertise (Cyranoski, 2018). Fourteen plans explicitly mentioned programs and initiatives to make it easier to attract foreigners with the requisite talent. For example, Czech Republic's plan said, *"Essential simplification of administration for admission of foreigners – researchers and students from abroad (visa duty, enrolment in studies, administration of doctoral studies, issues of taxes and insurance), revision of the Act on the Residence of Foreigners"* (Czech Republic AI Plan, 2019, p. 17). Whereas, Mexico's plan emphasised homegrown talent as, *"The recommendations in this report seek to remedy these areas with targeted policy recommendations such as visa schemes to incentivise homegrown talent to return, and training schemes to nurture future generations of tech talent"* (Mexico AI Plan, 2018, p. 13).

Thirteen plans referred to the initiative of transforming the procurement process in the public sector. Norway's plan states, *"The public sector ought to actively explore opportunities in the market in connection with procurements, and innovative public procurements should be used where appropriate"* (Norway AI Plan, 2020, p. 8). The procurement processes in the public sector are often cumbersome and do not easily allow agencies to adopt innovations in an agile manner. Serbia's plan noted *"The Public Procurement of Innovative Solutions implies the public sector's use of its purchasing power in order to act like an early adopter of innovative solutions that are still not available at a commercial level. On the other hand, the public procurement of innovative solutions enables the public sector to modernize public services and achieve savings at the same time"* (Serbia AI Plan, 2019, p. 18).

Eleven plans signalled the need to transform the business models of public sector agencies to develop readiness for AI adoption. For example, the Lithuanian plan discussed, *"The biggest obstacles to greater implementation of AI systems in the public sectors are the barriers to innovation. Public institutions are slower to adopt new technologies due to either a lack of proper funding or a slow bureaucratic procedures. In order to ensure the best quality of life for citizens in the digital age, the public sector* *will need to adopt a culture of innovation, especially in regard to AI"* (Lithuania AI Plan, 2019, p. 13). The need to rethink current operating models in the public sector is critical. Unlike previous generations of information technologies, which were mainly focused on improving efficiencies of processes, consider e-government initiatives, or make existing processes more accessible to stakeholders, such as through the deployment of mobile apps, AI has the potential to lead to significant innovations in how public agencies are designed and operated. Finland's plan noted, *"In order to move forward quickly and in order to be successful at the utilisation of artificial intelligence and other possibilities related to digitalisation, the government must invest purposefully in expertise and its development, and the application of new operating models in central government"* (Finland AI Plan, 2017, p. 56).

3.7.5.4 Financing. Public finance can play a critical role in stimulating AI activity within the economy. Our analysis revealed two types of public financing activities: a) supporting small and medium enterprises (SMEs) and startups and b) providing tax incentives for the private sector. Fifteen plans discussed both types.

Twenty-one plans referred to the government providing financial support to AI SMEs and startups directly or to facilitating access to funds from private financial institutions. India's plan notes, *"Support systems for AI based startups: Establish incubation hubs and venture funds specifically for AI startups in collaboration with State Governments"* (India AI Plan, 2018, p. 93). Serbia's plan noted, *"In addition, the implementation of the Program Supporting the Digital Transformation of the SME sector in 2019 is underway, with the goal of establishing an infrastructure for the support of SMEs and creating possibilities for development and application of AI for the optimisation of business processes and the enhancement of the business of individual SMEs"* (Serbia AI Plan, 2019, p. 15).

Sixteen plans called for the option to provide tax incentives to the private sector to stimulate research and development in AI. For example, Serbia's plan declares, *"The tax treatment of innovations is also important for the development of artificial intelligence. Amendments to the Corporate Profit Tax Law in 2018 caused positive developments in this area, as they enabled the recognition of expenses for research and development in the double amount, in case the research was conducted in Serbia. The same regulation reduced the profit tax rate from the company's income based on intellectual property created in Serbia from 15% to 3%"* (Serbia AI Plan, 2019, p. 19).

China's plan also referred to tax deductions, *"Through high-tech enterprises tax incentives and R&D additional deductions and other policies to support the development of AI enterprises. Improve the implementation of open data and protection-related policies"* (China AI Plan, 2017, p. 25).

3.7.6 Governance

The public sector has an important role to play when it comes to designing and implementing governance frameworks to support responsible innovation. Ideally, governance frameworks should promote the realisation of benefits and minimisation of harm when it comes to how AI systems are deployed in the public sector (Gasser & Almeida, 2017). Our analysis revealed six areas where plans called for attention to governance: 1) regulations, 2) risks, 2) social inequality impact, 4) security, 5) intellectual property rights protection, and 6) interoperability.

3.7.6.1 Regulations. All thirty-four plans discussed the need for nations to develop regulations around AI systems. For example, France's plan said, *"Certain sectors need to inform themselves well in advance about the specific regulations relating to the development of AI solutions, such as: the sector-specific regulations which apply to markets and financial stakeholders which fall under the control of the ACPR (Autorité de contrôle prudentiel et de résolution —French Authority for Prudential Supervision and Resolution) or the AMF (Autorité des marchés financiers—French Financial Markets Authority); the regulations concerning the security of information systems which fall under control of the ANSSI (Agence Nationale de la Sécurité des Systèmes d'Information —French National Cybersecurity Agency); and the regulations relating to the use of personal data operated by the CNIL (Commission nationale de l'informatique et des libertés — French Data Protection Authority)"* (France AI Plan, 2018, p. 34). Nations were naturally concerned about how to develop regulations around liabilities that arise from autonomous systems. The Czech Republic's plan noted, *"Preparation of an analysis of Czech legal regulations and implementation of European principles of liability for damage in relation to AI, especially for the operation of autonomous and collaborative systems and for phases of experimental and live operation with special emphasis on continuously self-learning systems, including possible introduction of compulsory insurance"* (Czech Republic AI Plan, 2019, p. 34).

3.7.6.2 Risks. Twenty-seven plans discussed the need to study the risks associated with AI systems. For example, Singapore's plan mentioned applying *"…multidisciplinary and human-centered approaches to study the systemic risks and long-term impact of AI and develop potential solutions to address them. Risk assessment in AI development should not be narrowly confined to the engineering disciplines, but also include sociologists, ethicists, economists, lawyers and policy makers. Today, Singapore's universities are actively studying the societal implications of AI, and we will tap on their expertise"* (Singapore AI Plan, 2019, p. 65). Denmark's plan echoed, *"On the one hand, the spread of artificial intelligence entails a risk of exacerbating existing cyber threats and creating entirely new risks. At worst, technologies using artificial intelligence could be influenced for malicious use. For example, artificial intelligence could be used to automate cyber attacks on critical infrastructure and on Danish companies"* (Denmark AI Plan, 2019, p. 26).

3.7.6.3 Social and Economic Inequality. AI systems can increase social and economic inequalities in populations. As discussed earlier, the nature of data used to train algorithms plays a significant role in the level of bias. We found discussions on social inclusivity and algorithmic fairness in plans, and 24 plans recognised that AI systems might exacerbate existing socio-economic inequalities. For example, Mexico's plan claims, *"The changes in work brought by automation will also have consequences for Mexico's policies on tackling inequality"* (Mexico AI Plan, 2018, p. 26). Similarly, the UK's plan said, *"Everyone must have access to the opportunities provided by AI. The Government must outline its plans to tackle any potential societal or regional inequality caused by AI, and this must be explicitly addressed as part of the implementation of the Industrial Strategy. The Social Mobility Commission's annual State of the Nation report should include the potential impact of AI and automation on inequality"* (UK AI Plan, 2018, p. 86).

3.7.6.4 Security. AI systems can be a threat to security in two broad ways: 1) intentional use of destructive AI (e.g., autonomous weapons) and 2) unintentional malfunctioning in AI systems (in autonomous cars etc.) that could damage humans, properties and natural resources. Twenty-one plans recognised that AI systems can be used to cause harm and the need to carefully consider the malicious use of the technology. For example, Denmark's plan mentioned, *"On the one hand, the spread of artificial intelligence entails a risk of exacerbating existing cyber threats and* *creating entirely new risks. At worst, technologies using artificial intelligence could be influenced for malicious use. For example, artificial intelligence could be used to automate cyber-attacks on critical infrastructure and on Danish companies"* (Denmark AI Plan, 2019, p. 26).

France's plan noted, *"One of the greatest concerns regarding developments in AI is the subject of lethal autonomous weapons systems (LAW). This is not a new discussion: indeed, France initiated it in 2013 within the UN Convention on Certain Conventional Weapons (CCW) which led to the creation of a group of government experts whose first session was held at the end of 2017"* (France AI Plan, 2018, p. 125).

3.7.6.5 Intellectual Property Rights Protection. Given the intensity of research and development efforts underway and the need to secure competitive advantages, 15 plans called out the need to develop protocols to secure intellectual property rights. For example, China's plan mentioned *"Strengthen the protection of intellectual property in the field of AI. Improve technological innovation in the field of AI, patent protection and standardisation of interactive support mechanism to promote the innovation of AI intellectual property rights. Establish AI public patent pools. Promote the use of AI and the spread of new technologies"* (China AI Plan, 2017, p. 26). Current intellectual property protocols have deficiencies when it comes to addressing computer-generated products and services (Davies, 2011). Norway's plan said that *"Intellectual property rights Protecting intellectual property rights is important for ensuring that the AI market develops in the right way. Any uncertainty about ownership of the various elements that make up solutions based on AI (data, development framework, pre-trained algorithms, etc.), how they are licensed or how access to the solutions is paid for, will have negative impacts"* (Norway AI Plan, 2020, p. 51).

3.7.6.6 Interoperability. Interoperability is essential when designing AI systems to take advantage of datasets across heterogeneous systems. Designing frameworks to promote interoperability across data, systems, and even systems of systems will play a key role in the public sector. The public sector can play the roles of a convener and an arbiter when it comes to the development of standards for the digital economy (Gasser, 2015). Eleven plans discussed the importance of AI system interoperability for the stakeholders (government, industry, academia, NGOs, and society) of the national AI ecosystem to operate in conjunction with each other. For example, the UK's plan stated, *"To organisations and businesses, it would provide a clear, consistent and interoperable framework for their activities, while for citizens and consumers, it would provide a recognised and trustworthy brand, reassuring them across the multiple domains of their life that they were getting a fair deal from AI"* (UK AI Plan, 2018, p. 125).

Italy's plan noted*, "The Plan was created to effectively guide the digital transformation of the country, becoming a reference for central and local administrations in the development of their information systems. It sets the fundamental architectural principles, the rules of usability and interoperability and rationalises ICT expenditure"* (Italy AI Plan, 2018, p. 13).

3.8 Discussion

Our analysis has uncovered that strategic AI plans are a rich source of information when it comes to understanding how nations see 1) opportunities to modernise the public sector and transform industries, 2) critical data and algorithmic elements that need to be managed, and 3) planning for capacity building and governance frameworks to support AI development efforts. We now discuss salient insights from our analysis.

China's strategic AI plan had the largest coverage of public sector functions. This was to be expected given the scale and impact of the public sector in China's economy. The central government of the People's Republic of China exercises significant authority over regional and local governments and has a unique ability to coordinate efforts across agencies due to its level of power and influence. As such, one can expect China to lead other nations when it comes to modernizing its public sector due to advances in AI.

The interest of nations in modernizing healthcare, both within the public sector and as an industry, was startling. Clearly, nations have realised the immense opportunities that AI provides to increase the effectiveness and efficiency of their healthcare systems. Healthcare also represents an industry that continues to push frontiers when it comes to the use of AI. Surgical robots, machine-learning algorithms for image processing, and chatbots for patient consultations, are just some of the many AI-enabled innovations already in use (Dash et al., 2019).

On the data front, it was heartening to see that the governments recognise the need to encourage data exchange between the public sector and external stakeholders. While most governments have open data programs in place, we believe that, to truly advance AI solutions for the public good, more is needed. Specifically, governments need to move beyond simply pushing data onto platforms to take a more proactive role and engage with stakeholders to identify data needs (e.g., what data is needed, in what form, at what frequency, etc.) and ensure that appropriate measures are in place to address privacy and security concerns. While most countries took an internal focus on data exchange, some recognised the value of sharing data across borders. We expect smaller nations (smaller in various dimensions, such as population size or economy) to lead the way in sharing data across borders for two reasons. First, these nations need to access large datasets to build robust AI applications. Second, these nations have the most to gain when it comes to collaborative funding investments in AI initiatives.

Regarding the AI algorithms, explainability was the most discussed concept. We expected this due to the fact that the level of transparency and explainability of algorithms that underlie a system is a critical differentiator between a traditional information system and an AI system. Increasing concerns about the black-box nature of algorithms (Bathaee, 2018) and evidence of unfair decisions, such as wrongly accused individuals from vulnerable social groups (Goldstein & Southall, 2019), only furthers the need to understand the issues surrounding how explainable and accountable AI systems can be.

Given the nature of strategic plans, we expected that all plans would discuss capacity development initiatives for AI. Among the various capacity development initiatives, most nations are focusing their efforts on infusing the relevant skillsets and knowledge competencies into the curriculum at higher education institutions and supporting multi-sector research initiatives. Similar to capacity development, we expected that all plans would highlight the role of the public sector in designing and maintaining governance frameworks to advance responsible innovation in AI. Most nations called for the need to develop capacity for agile regulations to keep pace with advances in AI.

While the plans were rich in information, we did find several key items missing from most plans. The first was any detail on how these plans were going to be implemented. Lack of details on implementation is a critical oversight because we are unable to assess how a nation will assign responsibilities and implement these projects. Second, there was a conspicuous absence of metrics in these plans. Metrics are vital when designing strategic plans to ensure that one knows the various milestones, how performance will be benchmarked, and even the targets that one is seeking to achieve. In cases where metrics were mentioned, they represented lofty ideals rather than tangible targets. Third, plans also tend to ignore funding realities. Technologies such as autonomous vehicles will significantly impact local government revenues (consider the drop-in income from speeding tickets), but the plans fail to acknowledge how AI will affect public finances. Finally, for nations to prepare themselves for AI, it is imperative that the public sector take the lead is driving the conversation on the future of the nation, its regions, cities, and communities when it comes to how AI will impact various fields, from the future of work to the transformation of healthcare. However, none of these plans had an associated communication plan that could begin to shape conversations and mobilise the citizenry around collective action on major issues.

Most of these plans remain far more aspirational than practical, yet in their content, we can see a glimpse of what lies ahead. Nations are poised to invest significant public resources in AI systems, and the AI arms race is well underway. While we remain excited about the prospects of AI to enable advanced solutions to address challenges and realise opportunities for innovation, our excitement should be tempered with the fact that the devil is in the details, and the public sector has a checkered track record of large-scale system implementations. However, the public sector sees the future to be rooted in AI; these plans represent a good first step in that direction.

3.9 Conclusion

Our work is exploratory in nature and represents only a first step in understanding how nations strategise their futures in the context of advances in AI. Future research is needed to delve more deeply into the components of these plans. Research is needed to more rigorously assess how substantially, or how superficially, critical concepts are covered in each plan. Given that nations have varying maturity when it comes to their digital government capabilities, future research can also look at variances in AI ambitions between nations with high maturity versus those with low maturity. Studying differences in the plans of countries that are in direct competition with each other (e.g., the US and China) versus those that are in cooperative networks (e.g., countries within the EU) might reveal differences in approaches as to how nations seek to go about building their AI capacities.

This study contributes to the field of technology management, public administration, policy analysis, and strategic planning in the public sector. We conducted a qualitative assessment of 34 national strategic AI plans and revealed the major themes they covered. For researchers, our study offers an initial examination of strategic AI plans and highlights the fact that this represents a valuable source of data for further analysis. For practitioners, our study provides a comparative assessment of plans that can be used to guide further strategic planning efforts.

Chapter 4: Study 2 - Exploration of AI Interests

4.1 Foreword to Study 2

Study 2 explored why the countries approached AI in a certain way. This study was based on a combination of findings from Study 1 (RQ 1: what is the AI affordance perception across the nations?) and a collection of secondary data of various socio-political factors of countries. This study presents the inspiration that national AI plans as a component of the national innovation system cannot work in isolation. The links between contextual conditions and national AI plans might not be evident; however, both are strongly related. Like general policies, AI policies do not have a fit for all list of policy instruments. The instruments used in the AI policies varied according to their context. The study suggests that national strategic AI plans are influenced by contextual factors and work as signals among governments and stakeholders (internal and external) to reduce information asymmetry. The study uses a mixed method research design to explore the links between AI affordance perception and contextual conditions that influence AI actualization. The study offers insights into policy analysis and understanding of the implicit message extracted from national AI plans and technology management regimes of countries.

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4.2 Statement of Contribution of Co-Authors

The authors listed below have certified that:

1. they meet the criteria for authorship and that they have participated in the conception, execution, or interpretation, of at least that part of the publication in their field of expertise;
2. they take public responsibility for their part of the publication, except for the responsible author who accepts overall responsibility for the publication;
3. there are no other authors of the publication according to these criteria;
4. potential conflicts of interest have been disclosed to (a) granting bodies, (b) the editor or publisher of journals or other publications, and (c) the head of the responsible academic unit, and
5. they agree to the use of the publication in the student's thesis and its publication on the QUT's ePrints site consistent with any limitations set by publisher requirements.

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Samar Fatima	Conceived, and design the study, selected and summarised the literature, collected data, performed data analysis analyses, drafted the manuscript.
Kevin C. Desouza	Principal supervision, conceived and designed the study, revised and edited the
James S. Denford	Guided and reviewed methodological rigour, data analysis and aided in the
Gregory Dawson	Provided support for theoretical lens, edited and reviewed the manuscript

4.3 Abstract

Since 2015, several countries have shown significant interest in artificial intelligence (AI) and have released national-level AI strategic plans. These plans reflect the country's rationale for embarking on AI. To identify what factors influence the AI approach of a country, this study employs the signalling theory to decode strategic national AI plans and understand each country's rationale. The study adapts the typology of signals and plots AI information given in national AI plans (AI-enabled public services, research, data, algorithmic ethics, governance) in a matrix of intentionality and veracity considering socio-economic and political conditions. Our findings indicate that countries with high democracy scores are more likely than less democratic countries to prioritise ethical and governance issues of AI, however, this is more pronounced in democratic countries with a lower technology base. The results also suggest that advanced research capability and data accessibility for AI is a precondition to developing a nationwide AI system.

4.4 Introduction

Nations are conducting significant initiatives for technology supremacy, especially when it comes to leading the artificial intelligence (AI) race. For example, China announced $12 billion spending on artificial intelligence (AI) in 2017 and predicted spending of $20 billion by 2020 (Hao, 2019b). Similarly, the US government has a budget of $2 billion in AI projects for the Department of Defense and quantum computing (Dwivedi et al., 2019). This race to AI is not limited to global superpowers. For example, the Government of Singapore has shown significant interest to pilot test autonomous vehicles for public transport (Trueman, 2019). As of January 2020, thirty-four countries have launched national strategic AI plans (Fatima et al., 2020b; Future of Life, 2020).

These national plans provide details of a country's strategy to harness the potential of AI and also indicate their approach towards economic, social, and policy-making paradigms related to AI technologies. Additionally, these plans highlight the coordination and assessment of such technology initiatives among various stakeholders of the society, e.g. public agencies and industry partners (Fatima et al., 2020b). In their study, Fatima et al., (2020b) found that these plans discuss the potential of AI and propose a course of action for AI development and implementation.

With the belief that AI is critical for economic and military dominance, countries are racing in intense competition to develop AI technologies (Kapetas, 2020). In this battle enabled by algorithms, unique patterns are emerging in various countries. Such as AI research culture of countries differs based on numerous political orientations. However, recently a major shift is witnessed on how countries sought to do AI research. (O'Meara, 2019). For example, China, one of the least democratic nations, is using a partnership approach with more democratic countries to promote AI research (The Economist, 2018). For example, Xi'an Jiaotong University's Institute of Artificial Intelligence and Robotics as one of the most highly respected institutes in AI research has a strong collaboration with the USA, Germany, France and UK institutes. In 2017, the 22nd conference on Architectural Support for Programming Languages and Operating Systems was held in Xi'an, China. As mentioned by conference organising committee, computer science conferences have largely been held in US or Europe previously, however, due to increasing number of research collaborations, they were able to conduct the conference in China (O'Meara, 2019).

We would have expected great commonality amongst the plans as, worldwide, governments are grappling with the same issues. However, Fatima et al., (2020b) found a significant variation among AI plans for inclusion or exclusion of an AI-related concept. For example, few plans emphasised the adoption of AI in the public sector more than in industry, similarly, some plans prioritised algorithmic ethics and AI governance while others did not. For example, France's AI plan explains the incorporation of ethics into the training of engineers and researchers studying AI (France AI Plan, 2018, p. 119). However, Russia's plan emphasised that the government would formulate ethical rules for human and AI interaction (Russia AI Plan, 2019, p. 17).

To study the differences between countries' approaches to AI planning, we draw on signalling theory, which postulates that a difference in information between two parties causes each of them to behave in different ways. The parties involved in signalling theory are the sender (has greater information) who choose whether or how to communicate (signal) the information that can impact or influence the behaviour of the receiver (has lesser information) (Connelly et al., 2011). Such signals given in AI plans need to be explored to understand why AI plans differ in intent and veracity and how these differences can impact the future of government with AI and the future of

AI in government. The reasons for such differences are not evident yet. The understanding of such differences has larger implications for AI development, AI policy-making, and strategic planning of economies.

However, it is not clear why the signals differ between countries and if the signals are intentional or inadvertent and whether they have high or low veracity. It is this question that motivates this research. As such, our research questions are:

RQ 1 – How do different types of governments signal using their AI plan?

RQ 2 – What are the veracity of these plans?

The study is structured as follows, first, we present the background of national AI plans and signalling theory and use this to generate our research propositions. In the methodology section, we define the dataset and fsQCA. After methodology, we report the findings and decision criteria for configuration recipes. Lastly, with insight for future research, we conclude the study.

4.5 Theory Development

4.5.1 National Strategic AI Plans

Strategic planning takes a future-oriented approach to develop organisational objectives and evaluating the performance against the objectives (Bryson et al., 2009). In the public sector, strategic planning provides a map of future direction and a course of action along with public agencies' capability to enhance public value (Poister, 2010). Studies on strategic planning in public agencies indicate that, despite budgetary, human and other resource constraints (Hatry, 2002), effective strategic planning in the public sector can bring meaningful change (Barzelay & Campbell, 2003; Hendrick, 2003).

Strategic planning is regarded as a black box until the content is operationalised into strategic plans (Bryson et al., 2009). According to Whittington et. al. (2006), to accelerate organisational change the tools between strategizing to organising are the strategic plans that interlink desired outcomes with deliverables. The approach by Whittington et.al (2006) focuses on features of strategic plans as artefacts of strategic planning. Similarly, Giraudeau (2008) analyzed the literature on strategic plans and declared strategic plans as tools for practising strategy and simulation tools to predict the future.

Strategic planning in science, technology, and innovation (STI) is different from general policymaking (Stine, 2009). The difference is mostly due to rapid advancements in STI as compared to other policies. Strategic planning for emerging technologies such as AI becomes more challenging for governments. Emerging technologies are largely discussed due to the uncertainty involved in their emergence (Wheatley & Wilemon, 1999). Since the development and practical implications of emerging technologies are not fully developed, therefore, the adoption of emerging technologies entails an element of risk and uncertainty (Bonnín Roca et al., 2017). The potential impact of emerging technologies on the economy and society plays a key role in the decision of emerging technologies adoption (Porter et al., 2002).

To develop and diffuse new (emerging) technologies, Metcalfe (1995) argues that a national system of innovation is inevitable. Through such an innovation system, governments design and implement policies to launch technological change. The national system of innovation presents the idiosyncratic institutional environment. The features of a national system of innovation vary from country to country (Freeman, 1995).

As a part of technology diffusion, technology, industrial and economic policies have been used as functional tools since half-century (Clark & Guy, 1998). Clark and Guy (1998) defined technology policy as a set of policies that are intended to persuade firms to develop, commercialise and adopt new technologies. They also presented the framework for technological progress and showed that science and technology, industrial, education, and macroeconomic policies all are bilaterally related to the technical progress of a country. They also suggested that for sustainable technological change, the importance of contextual conditions is undeniable. The contextual conditions of a country largely determine the way a country sought to launch technological change.

Technology policies as a component of the national innovation system cannot work in isolation. The links between contextual conditions and technology policies might not be evident, however, both are strongly related. For example, Genus and Coles (2005) performed constructive technology assessment and found that governance structure and public participation in science and technology debates and decision making can impact technology design and shape the overall system of technology-enabled innovation. Interestingly, recently launched national AI plans present a comprehensive approach towards such innovation. The national AI plans cover a thorough outlook on technology adoption as issues ranging from technical capacity building from computational systems design to governance conundrums, from AI implementation in the industry to public agencies and AI ethics by design to AI ethics by regulations, variety of aspects have been identified and discussed.

The release of national strategic AI plans is the most modern initiative to adopt AI at the country level. The first formal national strategic AI plan was released by Canada in 2017. However, the United States of America and South Korea released AI plans in 2016 but did not declare them as national AI plan specifically. In 2017, five countries including China, Canada, Finland, Japan, and the United Arab Emirates released their national plans. Most of the European countries in 2018 and 16 countries around the world formalised AI in 2019 and released national plans (Fatima et al., 2020b). Fatima et. al (2020b) analyzed 34 national AI plans and found six common themes among them which are AI priorities for implementation (public sector and industry), capacity development for AI (research, education, public agencies' business model renovation) in data accessibility, algorithmic ethics and AI governance.

In the study by Fatima et. al (2020), six main themes i.e. Use of AI in public services 2) Use of AI in Industries 3) Data for AI 4) AI Research 5) Algorithmic Ethics and 6) AI Governance with thirty-seven subsidiary codes of AI were identified. They assigned a score of 1 (0 for absence) to countries where a subsidiary code was present. The results indicated that some countries scored higher than others due to the presence of codes. For example, European Union countries exhibited greater concern for data sharing among them, whereas, countries with an authoritarian form of government, such as Russia and China emphasised building capacity for in-house data availability and accessibility. Fatima et. al (2020) describe the commonalities and differences between national AI plans based on the presence and absence of codes, however, the underlying reasons for such differences were not pointed out. The understanding of underlying reasons is important to consider while investigating countries' future with AI because these reasons predict the future trajectories. Hence, we caught interest in exploring why a country approached AI in the way it did and what this approach signals about the future.

4.5.2 *Signalling Theory*

Signalling is defined as a process by which one entity attempts to convey important information that can induce the other party to make a favourable choice (Spence, 1978). The entity sending the information (signal) is termed signaler and the entity for whom the signal is sent is the receiver (Connelly et al., 2011).

In his seminal work, Spence (1973) defined signalling as the behaviour demonstrated by a job applicant to support the selection decision by exhibiting their productive capacities that are not directly observable. The process of signalling occurs due to unequal information between two parties; the inequality of information is called information asymmetry. The core of signalling theory consists of the analysis of various types of signals and the situations in which they are used (Spence, 2002).

The signalling theory has been employed in vast areas of research. Such as in corporate governance studies to signal concern for society via financial statements to prospective investors (Zhang & Wiersema, 2009). Similarly, studies indicate the use of heterogeneous boards in recruitment to signal adherence to social values (Miller & Triana, 2009). In e-commerce studies, the use of signalling fits well because buyers have no access to the physical premise of the seller. The buyers rely on the signals given on the website and situations in which the signals are given to make a purchase decision (Mavlanova et al., 2012).

The typology of signals defines a 2 x 2 matrix of signals as shown in Table 4.1. This typology suggests that signal intention and signal veracity determine the properties of signals. The signal intention can be deliberate or inadvertent. Similarly, signal veracity varies from high to low. The typology formulates a matrix that compares signal intention and signals veracity with both types (Dawson et al., 2016).

Table 4.1 *Typology of Signals*

		Signal veracity	
		High	Low
Signal intention	Deliberate	Traditional signals	Opportunistic signals
	Inadvertent	Inadvertent disclosure signals	Mixed signals

Note. Adapted from Dawson et al. (2016).

Traditional signals are both deliberate and true. These signals are intended to reduce information asymmetry that is a core focus of signalling theory. *Inadvertent disclosure signals* transmit true information, but the sender does not send it deliberately. During inadvertent disclosure, true information is given that also reduces information asymmetry but not induced by the sender's intention. *Opportunistic signals* are not true and induced deliberately by the sender. Such false signals sabotage the objective of signalling theory and increase disadvantageous information asymmetry. *Mixed signals* transmit false information without the sender's deliberate intention. These signals can be taken anyway (true or false) by the receiver. Mixed signals can increase or decrease the disadvantageous information asymmetry (Dawson et al., 2016).

Signalling theory literature mentions use of signalling process in the public sector studies, however, it is a relatively new lens to study public sector interaction with citizens and other stakeholders (Raaphorst & Van de Walle, 2018). A pioneer work on policy reforms figured out that information asymmetry about the government's future intentions is the core reason for citizens and the private sector's insufficient credibility on government policy reforms. The study suggested that transmission of direct signals such as the speed of reforms can help the reform-minded government to gain the credibility of citizens and private sector partners (Rodrik, 1988).

Few studies, such as Goodsell (2000), referred to government agencies' magnificent building architecture and prime location as a signal to exhibit legitimacy and authority to citizens (Goodsell, 1977, 2000). Similarly, Raaphorst & Van (2018) drew on signalling theory to describe the communication between citizens and public officials and found how unobservable signals of trust can be translated into observable signals with both parties on the signaler and receiver sides. The findings of the study reinforced Spence's (2002) statement that the context in which signals are sent and received largely determines the interpretation (Raaphorst & Van de Walle, 2018).

However, the scope of these studies employing signalling theory in the public sector is limited to one signaler (government) and one or two receivers, i.e. citizens and private sector partners. In this study, we have taken a wide range of receivers including citizens, other countries, AI research centres, non-government regulatory entities e.g. OECD, EU.

4.5.3 *Proposition Development*

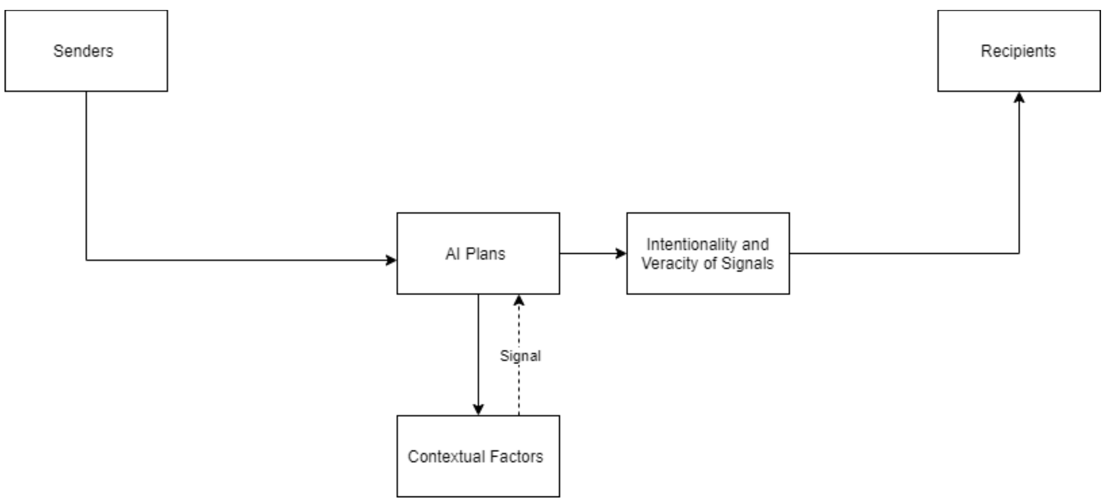
AI is the key to economic growth, national security, and strategic advantages, the competition between countries to dominate in AI is getting fierce. The development and implementation of AI technologies have become the national agenda. This national agenda is being propagated by governments through national AI plans. Countries like the USA and China are allocating billions of dollars to AI research and development of AI systems (Dwivedi et al., 2019). According to Castro et. al (2019), the USA leads the race for AI advancement despite China's enormous spending for AI development. USA's AI start-up ecosystem, production of computer chips, and high-quality AI research were declared some of the factors that help the USA is leading the competition.

However, in another report, China was declared to not only be the AI race-leading country but also surpassing the capabilities of the USA and European countries (Schmidt & Allison, 2020). China's command in both national and commercial security enabled by AI was revealed the reason to lead the race. The effective use of surveillance applications during the covid-19 pandemic has helped China to lead the AI trajectory (Schmidt & Allison, 2020). Similarly, the European Union has also shown a significant increase in AI investment deals from about 30 in 2011 to 350 in 2017 (OECD, 2018). Therefore, it is not possible to uncover the geopolitics of AI and determine what countries are in lead.

Also, to distinguish between technical capacity development and regulatory control development related to these emerging technologies is vital to understand the future of AI. For example, if a country fully deploys AI-enabled public services but public trust is damaged due to the government's tech-centric rather than citizen-centric approach, would such technological adoption likely sustain public value? A recent example of a public trust breach is where an autonomous system of the Dutch government wrongly accused more than 26,000 families of making fraudulent childcare benefits (BBC News, 2021; The Guardian, 2021a). To answer such wicked questions, national AI plans are a useful tool to predict what the future of AI holds. A policy does not exist in a vacuum rather it is influenced by the context in which it is designed, drafted, and implemented (Borrás, 2011). Innovation policy scholars have emphasised the inclusion of a mix of policy instruments to understand innovation at the national level (Branscomb & Florida, 1998). Policy instruments as intangible social constructs are defined in multiple ways. According to Lascoumes and Gales (2007), policy instruments are devices with technical and social dimensions that mediate between government and actors from policy design to policy implementation. The three types of policy instruments as defined by Borras (2011) are regulatory instruments e.g. (intellectual property rights) financial and economic instruments (tax exemptions) and soft instruments (public-private partnerships) (Borrás, 2011). Like general policies, AI policies do not have an "optimal" or fit for all list of policy instruments. The instruments used in AI policies vary according to their context (Borrás, 2011). Similarly, the objectives of AI plans are to inform internal and external stakeholders about AI initiatives. In terms of signalling theory, we define AI plans as signals, governments as signalers and internal and external stakeholders as receivers. However, the quality of signals varies depending on the contextual conditions of a country.

Not only each plan differs in showing intentions but also in some claims made are true while others are not. In this study, we are interested to figure out which claims are veracious with the existing information and which are not. The context of one country differs from the other, therefore no single set of policy instruments can be equally suitable for all countries. These contextual factors impact AI planning and the future of AI. The contextual factors could be several such as, the form of government (democratic or authoritarian), economic indicators, civil liberty, public participation in government decisions. Having mentioned that, we propose our model in Figure 4-1. Next, we define why the information given in AI plans is important.

Figure 4-1 *Signalling Theory and AI Plans*



We suggest that intentionality and veracity of the information on the AI initiatives are important for both; countries releasing AI plans (senders) and recipients of the information, i.e. internal and external stakeholders. AI plan releasing countries convey the information to reduce the information asymmetry and invite opportunities for collaboration of AI research, attract foreign AI experts, build regional data network, etc. By soliciting such information, AI plan releasing countries can highlight the information they deem favourable for AI development, implementation, or governance.

Similarly, internal and external stakeholders (termed as buyers in signalling theory) are those entities that can influence or be influenced by a country's approach to AI. For example, AI research centres find opportunities with similar research interests. Non-government regulatory entities such as Organisation for Economic Co-operation and Development (OECD) or World Economic Forum (WEF) observe the missing AI governance components and highlight governance-related issues. Therefore, reducing information asymmetry between countries and recipients of the information is a cornerstone for AI development, implementation, and governance.

However, reducing information asymmetry depends on the intentionality/deliberateness and veracity of the signals, and not all AI plans exhibit similar intentionality and veracity of signals. Further, the intentionality and veracity of signals are not straightforward to determine. We use three dimensions to ascertain the intentionality and veracity of AI signals to develop our typology table for AI plans (Table 4.1).

1. **Signal fit** - The extent to which the signal is correlated with unobservable quality (Busenitz et al., 2005; Zhang & Wiersema, 2009). For example, the tendency of a country to lower the spread of covid-19 can be signalled through their international border closure or open status. There is a logical connection between the number of international travellers entering a country with the number of covid-19 cases. We define unobservable quality as the contextual conditions of a country that directly or indirectly impact the policies. Further details on contextual conditions are given in the methods sections.
2. **Signal consistency** - The extent to which there is an agreement between signals from different sources (Fischer & Reuber, 2007). For example, if the democracy score of a country is higher, the tendency of having free and fair

elections at the stipulated time is also present. Both these factors democracy score and conduct of elections indicate a consistency among two political factors. However, the two sources of information can be related or unrelated. The source of signals and conditions in this study are countries. Thus, signal consistency in this regard is how aligned the claims made in AI plans are with contextual conditions of the country.

3. **Signal reliability** - The combination of a signal's fit and consistency (Arthurs et al., 2009). If there is a logical explanation and consistency between what signals indicate and contextual conditions, we refer to it as signal reliability. For example, the use of AI in public services signals citizen-centric AI. However, if the use of AI is abiding by rules of data protection and other governance-related issues, only then the signal would be considered reliable.

We refer to four types of signals as discussed in table 4.1. For example, in AI plans, the traditional signals with deliberate intention and high veracity can be a description of AI projects already initiated or information of budget amount allocated for AI research. The inadvertent signals with high veracity are the ranking of a country in digital literacy or the number of AI research publications per year. These signals even if not included in the plan are already available.

Likewise, if a plan claims that citizens will be included in the process of AI policy design while the contextual factor of citizen engagement rate in policy design is very low, such contradiction is regarded as an opportunistic signal. Mixed signals on the other hand are difficult to catch as the intention of the sender is not clear (whether deliberate or inadvertent). An example of mixed-signal in AI plans is the declaration of using anonymised public data in AI systems, while analysis of contextual conditions fails to depict the use of anonymised data. However, the reason for such inconsistency is not clear. Based on these statements, our propositions are:

- ***Proposition 1:*** *National AI plans signal contextual factors of countries*
- ***Proposition 2A:*** *The intentionality of AI plans (signals) is influenced by national contextual factors*
- ***Proposition 2B:*** *The veracity of AI plans (signals) is influenced by national contextual factors*

We propose that national AI plans (signals) as artefacts of strategic planning of countries (senders) transmit information to a wide variety of receivers (internal and external stakeholders). Employing signalling theory, we decode these signals to predict their intent and to judge their veracity. We consider socio-political and economic factors of a country and explore the link between these contextual factors and signals using Fuzzy Set Qualitative Comparative Analysis (fsQCA). Having done that, we identify the configuration models among the contextual factors and AI plans (signals)

4.6 Methodology

4.6.1 Approach

The approach used to study the national system of innovation must enable theoretical multiplicity where multifaceted phenomena can be explored (Park et al., 2020). To conduct systems perspective research, a configurational analytic approach such as Qualitative Comparative Analysis (QCA) is suggested as it uses both theory and method to identify the casual recipes for the occurrence of an outcome (Fiss et al., 2013; Levallet et al., 2020). QCA works with configurational approaches to find out which parts of the system (called conditions) are necessary or sufficient for the occurrence of an outcome (Rihoux & Ragin, 2009; Thiem et al., 2016). QCA was launched as an innovative research approach in Information Systems (IS) to explore complex causal relationships (Fichman, 2004).

Today, QCA is being used in several IS research as the main methodological approach (Park et al., 2020; Tsolakis & Tsekouras, 2016). We sought QCA as a suitable approach to explore the relationship between technology policies (AI plans) and socio-economic contextual factors. By employing QCA, we identify the causal complexities between AI priorities and contextual factors.

Among the types of QCA, we chose fuzzy-set qualitative comparative analysis (fsQCA). In fsQCA calibration of conditions and outcome ranges from 0 (non-membership) to 1 (full membership). Fuzzy sets offer both qualitative and quantitative insights. The calibration of data from 0 to 1 provides features of interval and ratio scales, while such calibration is performed using theoretical and substantive knowledge thus depicting vital qualitative features (Ragin, 2008).

The three steps involved in performing fsQCA are 1) preparation of dataset, 2) construction of truth table and 3) logical reduction of outcomes (Park et al., 2020). In the first step, data is calibrated on a scale of 0 to 1, the calibration standardises all variables on fully in to fully out in membership. The two important statistical measures considered in fsQCA are coverage and consistency of solutions (Denford et al., 2019). Consistency is the degree to which a relation of necessity or sufficiency between a combination of conditions and an outcome is met within a given set of data, whereas coverage is a measure of empirical relevance that captures the degree of overlap between sets or between a set and the overall solution space, again ranging from values of 0 and 1 (Ragin, 2008). Analysis in fsQCA produces three sets of solutions 1) complex solution 2) intermediate solution and 3) parsimonious solution. As a result of the analysis, core and peripheral conditions are identified. Conditions appearing in both parsimonious and intermediate solutions are considered core while those only in intermediate are considered peripheral. The positive dimension of a condition in a solution is deemed presence (core or peripheral) and the negative dimension of a condition in a solution is taken as absence (core or peripheral) (Ragin, 2008). Detailed information on data preparation is given in the next section.

4.6.2 Calibration and Principal Component Analysis (PCA)

The dataset used in the study has two components: conditions and outcomes.

4.6.2.1 Country Conditions. To determine the intention and veracity of signals (AI plans), we gathered information on the characteristics of each country. As fsQCA allows the use of numerical data (when standardised and calibrated), we used country characteristics from the Global Competitiveness Index of the World Economic Forum (WEF) (World Economic Forum, 2017). The most recently available values of variables (yearly, monthly, quarterly, etc.) are used in the study. Initially, we collected a total of 53 variables that define the socio-political and economic characteristics of the countries e.g. democracy score, diversion of public funds, government support for R&D etc. The initial dataset of characteristics with time, scale and value is shown in appendix H.

4.6.2.2 Plan Outcomes. The second component of the dataset is outcomes that have been taken from the appendix of the study “National strategic artificial intelligence plans: A multi-dimensional analysis” (Fatima et al., 2020b). This study analyzed national AI plans of countries and assigned a value to various components found in the plan. A total of five outcomes has been used in the study (dataset of outcomes is shown in appendix I). Fatima et. al (2020b) analyzed thirty four national AI plans and found common themes across them using content analysis. They coded data following Dey's (1993) guidelines and identified six themes with 37 subsidiary codes in them. The common theme among national AI plans are 1) Implementation of AI in public sector functions 2) Implementation of AI in industry sector 3) Data for AI 4) Algorithms 5) Capacity development for AI and 6) AI Governance. To ascertain the coverage of various codes within a plan, they assigned "1" for a code present in the plan and "0" if a code was not present in the plan. Based on the scoring of 0 and 1, they calculated the composite score for themes and countries and declared some plans more detailed (in terms of coverage of concepts) than others. Drawing on the findings of Fatima et. al (2020b), we prepared our dataset and used five themes from their analysis that are 1) Use of AI in public services 2) Data for AI 3) AI Research 4) Algorithmic Ethics and 5) AI Governance. We did not use the sixth theme i.e. use of AI in industry, since the scope of our study is limited to the use of AI in the public sector. The second component of data; outcomes data extracted from a secondary data source i.e. findings by Fatima et. al (2020b).

In the first step, we calibrate the data set of all country conditions. We use 0 and 1 as fully-out and fully-in values. We use logical reasoning based on the original formulation of each condition as suggested by Ragin (2008) to calibrate the data. We did not use means, minima, and maxima for calibration as these forms the weakest type of calibration. For example, the democracy score is 1 to 10 with 8-10 being defined as a full democracy. This suggests that a logical argument can be made for setting the fully-in point at 8 out of 10 as all cases above this are, by definition, fully democratic. Similarly, the scale defines hybrid as being between 4 and 6, making 5 the midpoint and cross-over between the two. Finally, while authoritarian (i.e. not democratic) is defined as 1 to 4, a case can be made for either setting fully-out as 4 (based on the scale) or 2 (based on parallelism with partial democracy) to calibrate the data.

To create composite variables (data reduction to capture the variance), we ran principal component analysis (PCA) using the calibrated data of country conditions. We found 17 variables that were grouped in 5 groups with all factors loading over 0.800, cross-loadings under 0.250, and 88.0% variance explained, making these highly consistent factors with strong explanatory power (Nunally, 1967). We named these groups according to their common features. Table 4.2 below presents the five groups and variables in each group with the factor-loaded value.

Table 4.2 *Principal Component Analysis of Country Conditions*

Conditions	Sub-conditions	1	2	3	4	5
Democracy	Democracy	0.980	0.059	0.024	-0.033	-0.009
	Voice and accountability	0.969	0.142	0.175	-0.025	-0.019
	Electoral democracy	0.939	-0.170	-0.074	-0.086	-0.070
	Freedom of elections	0.910	-0.140	-0.009	0.103	0.038
	Freedom of internet	0.855	-0.051	0.103	-0.222	0.072
Effective government	Trust in politicians	-0.140	0.955	0.167	-0.020	-0.049
	Government political stability	-0.008	0.941	-0.009	0.010	0.135
	Diversion of funds	0.062	0.932	0.222	0.090	-0.014
	Government future orientation	-0.195	0.908	-0.024	-0.004	0.104
	Judicial independence	0.106	0.856	0.231	0.023	0.066
Reform orientation	Reforms social	0.020	0.187	0.919	0.048	-0.140
	Reform society	0.096	0.080	0.887	-0.192	0.109
	Reform health and education	0.049	0.174	0.859	0.185	0.007
Political participation	Public participation (local)	-0.020	0.031	0.066	0.974	0.044
	Public participation (national)	-0.151	0.029	-0.029	0.968	0.045
Technical environment	Technical Environment for firms	0.052	0.088	-0.224	-0.078	0.816
	Public authorities support to R and D	-0.042	0.078	0.210	0.174	0.805

Next, we standardised (0-1) the calibrated values using PCA values and created composite values. The standardised composite scores of each country are shown in appendix J. The values shown in appendix J are fsQCA ready-to-use conditions data. To prepare a dataset of plan outcomes, we performed calibration and used theoretical reasons rather than taking minima, maxima, mean or median. The outcomes data have single values since there was no need for factor analysis. The fsQCA prepared plan outcomes data is shown in appendix K.

4.7 Results

4.7.1 Correlational Analysis

To identify if there were any dominant conditions, we first examined the correlations between country conditions and plan outcomes as shown in Table 4.3.

Table 4.3 *Correlation Matrix*

Country condition / plan outcomes	Democracy	Effective government	Reform orientation	Political Participation	Technical environment	Public Services	Research	Data	Algorithmic ethics	Governance
Democracy	1									
Effective Government	-.066	1								
Reform Orientation	.183	.590	1							
Political Participation	-.247	.101	.100	1						
Technical Environment	-.003	.468	.266	.218	1					
Public Services	-.231	.069	-.176	-.067	.180	1				
Research	-.019	.023	-.095	-.261	.143	.257	1			
Data	.121	-.130	-.066	-.157	-.190	.289	.555	1		
Algorithmic Ethics	.205	-.043	.007	-.081	-.284	.110	.267	.530	1	
Governance	.213	-.308	.006	-.275	-.253	.199	.416	.482	.547	1

The interesting insights from the correlation matrix (among country conditions) indicate that effective government was significantly correlated with reform orientation (.590) and technical environment (.468). However, reform orientation and technical environment were not correlated with each other (.266). Such results indicate the orthogonal connection between these three conditions. So while either reform-oriented governments are effective or governments in technical environments are effective, technical environment and reform orientation are generally unrelated to each other. Therefore, a country can be advanced in technical capabilities but still can avoid reformative initiatives. Another interesting and relatively less expected connection was found between democracy and effective government (-.066). The (negative) low value of the correlation score indicates that not all democratic countries are working effectively nor are only democratic countries perceived as the most effective.

Next, we discuss the correlation scores among outcomes. As expected, a strong correlation was found between data and research (.555) indicating that countries with high accessibility to data to be used for AI have greater concern for AI research. Similarly, a strong positive correlation was found between data and algorithmic ethics (.530). As expected, governance and algorithmic ethics also showed a positive correlation (.547) indicating that countries with high concern for algorithmic ethics signal formulation of AI governance mechanism.

No strong correlations were found between conditions and outcomes. This validates the choice of fsQCA as the suitable methodology since fsQCA works with causal recipes among conditions and outcomes and more relevant in situations like this where no clear one-to-one connection can be made and interpreted. In summary, the correlation matrix identifies no dominant conditions and proves the use of fsQCA as the right choice for investigating such phenomenon. Next, we present the results of fsQCA performed both for an aggregate AI plan outcome independently for each sub-plan outcome.

4.7.2 Configuration Analyses

To present the configuration analysis, we first create the indicators and their description to be used in configuration tables. The indicators and their descriptions are given in Table 4.4.

Table 4.4 *Indicators for Configuration*

Indicator	Description
⬤	Necessary presence of a core condition
●	Necessary presence of a peripheral condition
⨂	Necessary absence of a core condition
⊗	Necessary absence of a peripheral condition
Blank	The presence or absence of the condition does not impact the outcome
High	High outcome configuration
Low	Low outcome configuration

Note. Solutions that have the same core conditions are grouped by those conditions (i.e. High 1, High 2 or Low 1, Low 2) with configurations with the same core conditions but different peripheral conditions labelled with letters (i.e. 1A, 1B), while configurations that include two core conditions are labelled with both (i.e. 1A/2A).

4.7.2.1 Composite. Table 4.5 shows the configurational analysis for all of the country conditions and all of the components of the AI plan.

Table 4.5 *Composite Configurations*

	Comp High 1A	Comp High 1B/2A	Comp High 1C	Comp High 1D	Comp High 2B	Comp Low 1
Democracy	⬤	⬤	⬤	⬤		⨂
Effective government	●	●		⊗	●	●
Reform orientation	●		⊗	⊗		●
Political participation			●		●	●
Technical Environment		⬤		⊗	⬤	⨂
Raw coverage	0.615	0.587	0.358	0.291	0.583	0.177
Unique coverage	0.069	0.025	0.019	0.040	0.104	0.177
Consistency	0.840	0.822	0.878	0.963	.831	0.955
Solution Coverage			0.906			0.177
Solution Consistency			0.816			0.955

As shown, equifinality, which refers to multiple paths for achieving the same outcome, and causal complexity, that many different “recipes” exist, are present with our high configurations. While democracy is seen in most of the AI plans, it is not seen in all of them and the variety of other factors indicates high casual complexity. Not surprisingly, all our countries except UAE (the single, authoritarian and low-technology country in the low solution) are found in one of our configurations and that indicates that there are multiple ways to develop an AI plan. Since the composite AI plan index does not differentiate to a great extent the various countries, and so we delve deeper by looking at the five different components of the AI plans.

4.7.2.2 Public Services. Table 4.6 shows the configurational analysis for Public Services.

4.7.2.3

Table 4.6 *Public Services Configurations*

	PS Low 1	PS Low 2A	PS Low 2B	PS Low 3A	PS Low 3B
Democracy	●		•	•	
Effective government	•	•	⊗		•
Reform orientation	●	•	⊗	⨂	⨂
Political participation		•		●	●
Technical environment		⨂	⨂		•
Raw coverage	0.625	0.346	0.272	0.355	0.315
Unique coverage	0.243	0.015	0.042	0.017	0.010
Consistency	0.847	0.976	0.893	0.863	0.873
Solution coverage			0.830		
Solution consistency			0.810		

For high public services (Public Services), no solution was generated. However, low public services had all but two configurations load. The findings suggest that no countries in the sample had deployed AI for public services. Looking specifically at the output, it is Low1 that dominates with the greatest raw and unique coverage. The very small unique coverage in 2A/2B and 3A/3B shows that these paired configurations share a great deal of commonality with each other; it is also worth noting that they had low unique coverage in the parsimonious solution too. Essentially, almost all the solution space is covered by nations that lack AI for public services.

4.7.2.3 Research. Interestingly, no configurations – high or low – were generated (and thus no table is shown). This is a very interesting result as it means that the countries' conditions do not differentiate in the area of research. These findings suggest that the population of all countries with AI Policies are very strong in AI research/research strategy & policy. Also, it implies that strong research and research policy is a precondition to developing a national AI plan. Since no parsimonious and intermediate solutions were generated for research and ~ research, therefore, it is worth noting that AI research orientation is common across all countries, irrespective of their characteristics.

4.7.2.4 Data. The configurations for Data are shown in table 4.7.

Table 4.7 *Data Configurations*

	Data High 1A	Data High 1C	Data High 1D	Data High 1B/2A	Data High 2B
Democracy	⬤	⬤	⬤	⬤	
Effective government	●		⊗	●	●
Reform orientation	●	⊗	⊗		
Political participation		●			●
Technical environment			⊗	⬤	⬤
Raw coverage	0.515	0.300	0.240	0.491	0.489
Unique coverage	0.070	0.017	0.032	0.024	0.089
Consistency	0.868	0.912	0.985	0.850	0.860
Solution coverage			0.780		
Solution consistency			0.867		

Equifinality and causal complexity were present in our high data configurations. The output of the fsQCA standardised test showed that the greatest raw coverage is High 1A with democracy as core and effective and reformative government as peripheral conditions for data. The smallest raw coverage is High 1D where democracy is suggested as core presence and participative, reformative and effective government as a peripheral absence for the outcome (1) of data, while democracy was the most frequently seen factor, it was not present in all configurations.

The results of the data had close similarities to research configurations. However, the only point of difference is that all data did not show a high outcome (1). The exception was the UAE. which is a non-democratic and lower-tech environment. One probable reason for this is UAE's recent heavy investments in AI are significant, however, it has not yet caught up to countries that started earlier. Again, this is a single country outlier and there is almost uniform adoption of AI data policy in the population of nations with AI policies. In the second part of the analysis ~Data had no configurations to show the low outcome (0). Like research, data also indicates that availability and accessibility of data for AI is a feature common across AI plan releasing countries. This finding also signals the importance of data to build AI capabilities.

4.7.2.5 Algorithmic Ethics. The configurations for Algorithmic Ethics are shown in Table 4.8.

Table 4.8 *Algorithmic Ethics Configurations*

	Ethics High 1A	Ethics High 1B	Ethics High 1C	Ethics Low 1	Ethics Low 2
Democracy	●	●	●	⨂	⨂
Effective government	•	•	⊗	•	•
Reform orientation		•	⊗	⨂	•
Political participation	•			•	•
Technical environment	⨂	⨂	⨂	•	⨂
Raw coverage	0.320	0.315	0.262	0.160	0.128
Unique coverage	0.016	0.032	0.086	0.055	0.022
Consistency	0.877	0.826	0.776	0.840	0.825
Solution coverage		0.434		0.183	
Solution consistency		0.814		0.857	

Algorithmic ethics found the most diverse and therefore most interesting results. Non-democracies are all right at the bottom of the truth table (truth tables are given in appendix L) but, interestingly, those democratic paragons in the public services truth table are not represented here. There is visibly a combination of democracy and a low technical environment that is important – New Zealand, India, Lithuania, Spain, Serbia, Czech Republic, Mexico, Italy, Uruguay. The results underpin several reasons for low tech and high democratic countries.

Firstly, the absence of a strong national technical base indicates that the country is focused on ethical issues to prevent external actors from applying AI tools and techniques to the nation. Secondly, such a focus on algorithmic ethics lays the foundation of ethical innovation because AI as the industry has not developed yet. Thirdly, countries with average and high democracy scores are highly likely to anticipate and mitigate the risks associated with the use of AI in wake of AI malfunctioning incidents. To gain and retain public trust in AI system deployment, these countries signal higher concern for algorithmic ethics.

In the high outcome of algorithmic ethics (1), some of the high democratic countries such as Australia, Belgium, Canada, Denmark, Estonia, Korea, Luxembourg, Malta, Netherlands, Norway, Portugal, and the United Kingdom indicated the presence of all conditions but still did not result in the high outcome of algorithmic ethics. This finding signal that despite having high democracy, effective, participative, and reformative government, concern for algorithmic ethics is largely determined by the technical environment. Countries with high technical environments seem less prudent about algorithmic ethics as compared to those with low technical environments. This phenomenon is quite evident in the solution. The greatest raw coverage is High 1A where democracy is shown as core presence and technical environment is core absence.

In the low outcome of algorithmic ethics, it was non-democratic countries at the top of the list of those without algorithmic ethics policies, which would tie into their authoritarian use in public services – Russia and UAE are the two in the low algorithmic ethics. The overall assessment of algorithmic ethics shows that democracy and the technical environment play a significant role. Surprisingly, a low technical base reinforces the cautious intentions to inculcate algorithmic ethics in national AI plans.

4.7.2.6 Governance. The configurations for AI governance are shown in Table 4.9.

Table 4.9 *Governance Configurations*

	AI Gov High 1	AI Gov High 2	AI Gov High 3A	AI Gov High 3B/4A	AI Gov High 4B	AI Gov High 5	AI Gov Low 1
Democracy	⬤	●	⬤	⬤	●	⨂	⨂
Effective Government	●	●	●	⨂	⨂	●	●
Reform orientation	⬤			⊗	⊗	⨂	●
Political participation		⨂	●		●	●	●
Technical environment		●	⨂	⨂		●	⨂
Raw coverage	0.577	0.296	0.273	0.298	0.257	0.106	0.168
Unique coverage	0.177	0.023	0.034	0.012	0.004	0.054	0.168
Consistency	0.821	0.884	0.942	0.952	0.917	0.874	0.842
Solution coverage				0.781			0.168
Solution consistency				0.829			0.842

Equifinality and causal complexity are again high in AI governance and this suggests that many paths are possible for achieving this condition but challenge interpretation. Referring to the outcome table, the highest raw coverage is found in solution High 1 where democracy and reform orientation are core presence for AI Governance. It was mostly non-democratic countries clustered at the bottom of the Governance truth table and the top of the low Governance one, but with only one showing up in the low Governance solution. Again, this suggests that authoritarian governments are less concerned about unrestricted AI developments than democratic governments in a similar way that they are more likely to use public services for control purposes. On the low side of the Governance outcome, only one country, UAE was present again.

According to the truth table of high Governance, democratic countries dominate with a range of other combinations of factors. These findings suggest that democratic governments recognise the benefits of good governance in managing technology with far-ranging societal and ethical implications such as AI. This finding pairs well with the algorithmic ethics one. The interesting insight of the Governance truth table is that countries with high democracy and low technical environment cover the first few rows of the truth table; these are Lithuania, New Zealand, Czech Republic, Serbia, Spain, Uruguay, India, Italy, and Mexico. The underlying reason to prioritise governance among technically low capability countries is also because of the deliberate effort to develop AI capabilities with a strong governance mechanism in the first place.

4.8 Discussion

Our research questions were to decode the information (signals) given in AI plans considering various contextual conditions and predict the pattern of AI in countries. To discuss the fsQCA results, we refer to the signalling theory and recall the four types of signals discussed in earlier sections of the study. The four outcomes used in the study are 1) Public services 2) Research 3) Data 4) Algorithmic ethics and 5) Governance.

4.8.1 Criteria to Determine Intentionality and Veracity

The criteria to determine the intentionality and veracity of outcomes is selected as follows:

Table 4.10 *Criteria to Determine Intentionality and Veracity*

		Signal veracity	
		High	Low
Signal intention	Deliberate	1. Expressed in plans (Outcomes) 2. Established in contextual factors (conditions)	1. Not expressed in plans (outcomes) 2. Established in contextual factors (conditions)
	Inadvertent	1. Expressed in plans (outcomes) 2. Not established in contextual factors (conditions)	1. Not expressed in plans (outcomes) 2. Not established in contextual factors (conditions)

As discussed in the theory development section, signal fit, signal consistency and signal reliability help in determining the intention and veracity of signals. We found signal fit among signals and country conditions when there existed a logical explanation in terms of established knowledge. For example, democratic countries are more likely to exhibit concern for AI governance. Due to the increased involvement of the public in governmental decision-making, chances of concern for AI governance e.g. data privacy and fair and equitable treatment by autonomous systems are more likely to occur. Thus, we used a logical explanation of the outcome in deciding signal fit.

To determine signal consistency, we used an empirical approach and found out which of the signals agreed with contextual data. The determination criteria for signal consistency was based on evidence found from empirical data i.e. signals data and conditions data. Meanwhile, signal reliability was determined using a combination of both signal fit and signal consistency.

Using findings of Table 4.10, we placed signal fit, consistency, and reliability in Table 4.11. A higher value of fit, consistency and reliability are shown by plus sign (+) and a lower value of the three concepts is shown as a minus sign (-).

Table 4.11 *Signal Assessment*

		Signal veracity	
		High	Low
Signal intention	Deliberate	Signal Fit (+) Signal Consistency (+)	Signal Fit (-) Signal Reliability (-) Signal Consistency (-)
	Inadvertent	Signal Consistency (-) Signal Fit (+)	Signal Reliability (-) Signal Consistency (-) Signal Fit (+ or -)

Next, we present how national AI plans (outcomes) are categorised in terms of signal fit, signal consistency, and signal reliability about contextual conditions. The study has five outcome variables, defined as signals i.e. AI Research. AI Data, Algorithmic Ethics, AI Governance and Use of AI in Public Services. In this section, we categorise these signals in the template of Table 4.11.

The first signal is AI research. The analysis showed that the contextual conditions of all countries are in full agreement with the claims made in the national AI plans. The population of AI plans releasing countries has shown that building research capabilities are a precondition to developing AI. Bolstering AI research is vital to develop the national AI landscape. It was one of the most dominating themes found in almost all AI plans (Fatima et al., 2020b). Thus, AI research counts as a high signal fit (+). Also, the analysis showed that there is consistency between information given in signal and contextual conditions, therefore, the signal consistency for AI research is also high (+). Based on the presence of high signal fit and high signal consistency, we categorise AI research as a traditional signal with high intention and high veracity as shown in quadrant 1 of Table 4.12. Traditional signals reduce information asymmetry and fulfils the objective of signalling theory (G. Dawson et al., 2016). By highlighting AI research capabilities, countries showcase their research priorities to relevant stakeholders such as citizens, technology companies, sponsors and academicians. Moreover, as a traditional signal, AI research also indicates its role as a prerequisite to developing AI at the national level.

The second signal is AI data or data required to build AI systems. Data works as fuel for AI systems, thus shows a high signal fit (+). The role of data for AI system development has been well recognised by AI plans (Fatima et al., 2020b). Upon investigation of the information about data in AI plans, we noticed that data signals are largely validated by contextual conditions, indicating a high signal consistency. co. One exception was found among authoritarian countries – UAE. Results of data suggest that the signal has high signal fit (+) and high signal consistency (+). Like AI research, data is a primary factor for countries to develop and deploy AI systems. Meanwhile, data accessibility was found highly prevalent among democratic countries. We suggest data signals as one of the traditional signals with high intention and high veracity. Data is a resource required for building AI capability and AI plans indicated use and accessibility of data and contextual conditions are found in agreement with such claims. The data signal is also categorised in the first quadrant as signal fit and signal consistency are both on the higher end.

The third signal is Algorithmic Ethics. The results indicated that democratic countries have shown greater concern for algorithmic ethics that shows a high signal fit (+). However, among democratic countries, countries with low technical capability topped the list. This indicates that countries, with high technical capabilities, were not in full agreement with contextual conditions indicating a low signal consistency (-). The results also indicate that countries with low technical capabilities are proactive in building ethics by design since they have to lay the foundation for technology (AI specifically), while those with a strong AI foundation might assume it a challenge to re-build systems with ethics by design, this indicates lack of consistency between both sources of data. Thus, democratic countries indicate the emission of inadvertent signals for concern for AI ethics.

Similarly, the results indicated authoritarian countries have shown less concern for algorithmic ethics that depicts a high signal fit with contextual information (authoritarian countries have less involvement of the public in decision making and eventually lesser concern for ethical implications of AI). Meanwhile, the signal consistency is low as plans claim to make higher concern for algorithmic ethics but are not validated by the contextual information. Therefore, authoritarian countries also indicate the emission of inadvertent signals. The algorithmic ethics signals are placed in the second quadrant of the intention and veracity matrix i.e. Table 4.12.

The fourth signal is AI governance. There are considerable similarities between results of algorithmic ethics and governance, and both are placed in the second quadrant of the matrix (Table 4.12). Democratic and authoritarian countries showed similar patterns for AI governance as shown for algorithmic ethics. Democratic countries with low technical capability have shown greater concern for AI governance (high signal fit and low signal consistency). Meanwhile, authoritarian countries depicted lesser concern for AI governance (high signal fit and low consistency). Algorithmic ethics and governance place in the category of inadvertent signals. Inadvertent signals as discussed in the theory section, reduce information asymmetry and fulfil the objective of signalling theory but the disclosure of this information is not induced by the sender. For algorithmic ethics and governance, the true information is disclosed by analysis of contextual conditions. However, AI plan releasing countries didn’t intend to disclose because there is no consistency among the two sources of data. Meanwhile, inadvertent signals do not indicate manipulation by the sender that might occur in opportunistic signals.

The last signal is Use of AI in public services. This signal indicates various interesting insights. As the use of AI in Public services is extensively discussed in national AI plans (Fatima et al., 2020b). It was expected that contextual conditions of countries will validate such signals, however, the results showed that countries have not yet prioritised AI-enabled public services for citizen support. For authoritarian countries, the use of AI in public services was not expected (low signal fit), however, two authoritarian countries indicated the use of AI in negation set of fsQCA tests, indicating low consistency and low reliability of signals. According to signal fit, consistency and reliability, the veracity of these signals was very low with a high intention. Such a combination of the typology of signals is considered opportunistic signals. Thus, the use of AI in public services in authoritarian countries is placed in the third quadrant of the matrix that indicates the opportunistic nature of signals (Table 4.12). This trend indicates the use of AI for citizen control and surveillance more than citizen support in authoritarian countries, and the signalling is likely involuntary and hence an opportunistic signal. We placed authoritarian countries' use of AI in public services in the third quadrant with low signal fit, low signal reliability and low consistency.

Opportunistic signals falsely sabotage the objective of signalling theory and increase disadvantageous information asymmetry. For example, the information given in AI plans that do not turn to be true can increase information asymmetry among stakeholders who are users of such information. The information asymmetry has not only the tendency to slow the process of AI deployment but can also misperceive the AI priorities.

The results of democratic countries indicated low use of AI in public services. However, the plans made claims about the use of AI in public services that indicate a high signal fit. The results did not indicate the use of AI with contextual conditions. Also, the intention of democratic countries falls in the inadvertent quadrant as claims were about but not verified by the contextual conditions. Therefore, the use of AI in public services for democratic countries is placed in the fourth quadrant of the matrix and these signals are labelled as mixed signals as intention and veracity of signals are difficult to ascertain.

One reason for less validating signals (mixed signals) for AI in public agencies is the inflexibility in public agencies' business models to design and deliver AI-enabled public services. The intentions to use AI in public services are deliberate and abundantly discussed in the AI plans, however, the current state of contextual conditions shows that public agencies are not yet ready to fulfil such plans. This highlights the need to renovate the business models of public agencies to develop readiness for AI. Based on the analysis, we suggest that signals of AI in public services in democratic countries are likely opportunistic.

Table 4.12 *AI Plans Intention and Veracity Matrix*

		Signal veracity	
		High	Low
Signal intention	Deliberate	Research data	Public services (authoritarian)
	Inadvertent	Algorithmic ethics governance	Public services (democratic)

Note. Adapted from Dawson et al. (2016).

Summarizing the AI Plans Intention and Veracity Matrix, countries want to share information on their research and data initiatives for AI. The reason is that they seek potential collaboration opportunities about research or data sharing. Further research with highly relevant conditions for data (e.g. number of data generated in a day, government share in the generated data) and research indicators (e.g. number of international conferences, the proportion of foreign speakers, and topics covered in conferences) can better predict what kind of technologies are sought to be implied in countries.

Algorithmic ethics and governance issues related to AI are plotted in the inadvertent signals category. This finding is most exciting to be explored further. Democratic countries led authoritarian countries about algorithmic ethics and governance. However, among these countries, those with a low technical environment topped the list. We suspect that this may be due to a low-technology country having to grapple with such issues for the first time. However, further research can further investigate why the technical environment hinders (does not support) algorithmic ethics.

This finding is very useful for AI capability developing countries since the truth table listed countries such as New Zealand, Lithuania, Italy, and India, etc. at top of those that intend to enable algorithmic ethics and their contextual conditions also are in the right direction. As mentioned earlier, the geopolitics of AI is launching new trends, this is another influential one. Where technology advanced countries US and China are building AI capabilities (advanced research and system design), countries who are lagging, such as New Zealand, India and Italy, are building capability along with adherence to governance issues. It is important to reiterate that merely building AI capabilities would not help in leading the race rather ensuring a sustainable technology adoption process.

Another thought-provoking finding is the country's ambiguous status on the use of AI in public services. All countries irrespective of their democracy scores have given mixed/opportunistic signals about AI-enabled public services. One of the core objectives to adopt AI at the national level is to improve the quality of life of citizens. However, this objective has not been witnessed through the findings. Authoritarian countries rather showed a negative connection with the negation of AI in public services, which indicates that the use of AI seems to control the citizens instead of facilitating them. However, a further investigation with more relevant indicators of AI in public services can support or deny the proposition that emerged out of this study.

4.9 Limitations and Conclusion

As with all studies, this one has certain limitations. First, we had no way to validate that the plans were developed using any kind of consensus in the various countries but have no reason to believe that the plans do not represent the intentions of that country. Second, our dataset was limited to those countries that have actually produced a plan and cannot infer why a country might not have already developed one.

This study employs signalling theory to explore how national AI plan releasing countries view AI and to what extent their contextual conditions are related/unrelated to these plans. To do so, we used a fuzzy set qualitative comparative analysis to decode the national AI plans according to a set of socio-political and economic conditions. The study uses conditions data from WEF and outcomes data from the analysis of 34 national AI plans (Fatima et al., 2020b). After performing statistical processes to ensure rigour (exploratory factor analysis, principal component analysis and calibration of values), we prepared the data for fsQCA. Using fsQCA software, we generated the truth tables and conducted logical reduction to discuss the presence and absence of core and peripheral conditions in the causal recipes.

According to our results, strong technological and data capabilities underpin the ability of nations to deploy AI capabilities. For those nations that have fielded AI policies, AI is used by governments to reinforce their underlying tendencies. Democratic countries signal to use AI for further transparency and ensure they are well-governed and used effectively. Conversely, authoritarian countries signal to use AI to control and eschew governance and ethics. This study uses five independent outcomes (public services, research, data, algorithmic ethics, and governance) and general socio-economic conditions chosen for contextual factors.

The current study gives a solid base to further examine these contextual factors in the development of AI policy across nations. The study takes initiative in reading the between the lines messages as emitted from AI plans. These indirect signals can not only inform stakeholders about agenda of countries towards AI but also a guiding tool for countries who have not released national AI plans. By incepting the debate on reading signals from national AI plans, the study opens vast areas to be explored in future research.

In future research, each outcome can be investigated separately with a set of context-specific conditions. Also, since the study considers the AI initiatives as mentioned in national plans, it is important to investigate the feasibility of such initiatives. For example, how well the countries are capable to develop, and diffuse AI-enabled systems. For such exploration, computational capabilities of countries such as the availability of supercomputers can be an indicator to investigate in future research. Similarly, other indicators to gauge feasibility of AI initiatives can be exploration of AI workforce composition.

We conclude the study with the reflection that on the surface the plans depict all manner of honourable goals for racing to AI implementation but our deeper examination into the intentionality and veracity of the plans reflects a far more complex reality.

Chapter 5: Study 3 - Design and Evaluation of Public AI Canvas

This chapter comprises the peer-reviewed journal study titled *"Public AI Canvas for AI-Enabled Public Value: A Design Science Approach"* accepted for publication in Government Information Quarterly and is in press. This study presents the design and empirical validation of an artefact designed for AI affordance actualization.

5.1 Foreword to Study 3

In Study 3, a public AI canvas (PAIC) for AI-enabled value creation in public agencies was designed and evaluated. This study considered the issues related to AI-enablement, public value and social guidance for AI deployment in public agencies through three distinctive layers. The designed artefact was empirically validated in two steps, that is, demonstration of the artefact on an existing case study from Partnership for Public Services and conduct of 15 expert interviews to evaluate the artefact's completeness, its fidelity with the real-world, its internal consistency, the level of detail and robustness. The findings of empirical validation indicated the agreement of expert interviewees on three layers of the artefact and the respective elements. This study contributes to existing knowledge on the deployment of AI in public sector agencies by innovating their business models in a socially responsible manner. This study also extends knowledge of the design science research methodology's use in digital innovation.

This study has been accepted for publication in the Government Information Quarterly and is under publication process.

Fatima, S., Desouza, K. C., Buck, C., & Fielt, E. (2022). Public AI Canvas for AI-Enabled Public Value: A Design Science Approach. *Government Information Quarterly* (in press)

5.2 Statement of Contribution of Co-Authors

The authors listed below have certified that:

1. they meet the criteria for authorship and that they have participated in the conception, execution, or interpretation, of at least that part of the publication in their field of expertise;
2. they take public responsibility for their part of the publication, except for the responsible author who accepts overall responsibility for the publication;
3. there are no other authors of the publication according to these criteria;
4. potential conflicts of interest have been disclosed to (a) granting bodies, (b) the editor or publisher of journals or other publications, and (c) the head of the responsible academic unit, and
5. they agree to the use of the publication in the student's thesis and its publication on the QUT's ePrints site consistent with any limitations set by publisher requirements.

In the case of chapter 5: Design and Evaluation of Public AI Canvas. The paper is accepted for publication in Government Information Quarterly, Fatima, S., Desouza, K., Buck, C., & Fielt, E. (2022). Public AI Canvas for AI-Enabled Public Value: A Design Science Approach

Samar Fatima	Conceived, and design the study, selected and summarised the literature, drafted the manuscript, revised and edited the manuscript
Kevin C. Desouza	Principal supervision, conceived and designed the study, revised and edited the
Christoph Buck	Guided methodology design and aided in the interpretation of findings
Erwin Fielt	Provided support for understanding the theoretical lens, edited and reviewed the

5.3 Abstract

Public agencies have a strong interest in artificial intelligence (AI) systems. However, many public agencies lack tools and frameworks to articulate a viable business model and evaluate public value as they consider investing in AI systems. The business model canvas used extensively in the private sector offers us a foundation for designing a public AI canvas (PAIC). Employing a design science approach, this study reports on the design and evaluation of PAIC. The PAIC comprises three distinctive layers: (1) the public value-oriented AI-enablement layer; (2) the public value logic layer; and (3) the public value-oriented social guidance layer. PAIC offers guidance on innovating the business models of public agencies to create and capture AI-enabled value. For practitioners, PAIC presents a validated tool to guide AI deployment in public agencies. [1]

Keywords: artificial intelligence, business model canvas, public agencies, public value, design science

5.4 Introduction

With rapid advancements in artificial intelligence (AI), the public sector has shown great interest in AI deployment (Sharma et al., 2020). However, these are still early days when it comes to understanding the full potential and associated risks for deploying AI systems in the public sector (Agarwal, 2018; Berryhill et al., 2019; Danaher et al., 2017; Engin & Treleaven, 2019; Wang et al., 2021). AI systems, if deployed as intended, enhance public value but if AI systems do not function as intended, they can destroy public value (Desouza, 2018; Desouza, Dawson, et al., 2020; Mikalef et al., 2019; Mikhaylov et al., 2018b). Therefore, it is important to develop AI deployment frameworks for the public sector that facilitate enhancing public value.

Creating public value through technology requires agencies to carefully consider several elements of their business models (Ranerup et al., 2016). To date, the literature has scant solutions for how public sector agencies should articulate and evaluate public value when investing in AI systems. In the private sector, there are various tools, such

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[1] First version of the canvas was presented at 54th Hawaii International Conference on System Sciences and was nominated for best paper award.

as the business model canvas (BMC), to articulate the business logic of an agency to create and capture value. BMC is a visual tool that outlines an entity's business logic and identifies the critical components of a business (Osterwalder & Pigneur, 2010). If deployed in public agencies, such a tool could offer public managers a framework for effectively articulating the value logic associated with investing in AI systems (Budler et al., 2021).

The original BMC is not suitable for public agencies because of the core differences between public and private sector organizations (Ranerup et al., 2016). Therefore, by drawing on BMC, we designed a BMC for public agencies to create and deliver AI-enabled public value. Thus, our aim is to design an artifact for creating AI-enabled public value, and postulate our research question as: "How can an artifact be designed for public agencies creating AI-enabled public value?" The artifact is named public AI canvas (PAIC).

To answer this question, we used design science research methodology (DSRM) (Peffers et al., 2007). According to DSRM, an artifact, object, or instantiation is designed to solve a problem. DSRM is widely applied in information systems research (Hevner et al., 2004). We follow the guidelines in Peffers et al. (2007) to conduct our research.

Employing the DSRM, after several design iterations we construct our first PAIC. This PAIC is then validated in two steps. We first demonstrate the utility and completeness of the artifact by applying the PAIC on a publicly available case of AI deployment in the public sector published in Partnership for Public Services (PPS). The case is titled "Into the Storm: Using Artificial Intelligence to Improve California's Disaster Resilience." This case presents the use of an AI software called WIFIRE by the city and county of Los Angeles to make predictions about wildfires. Next, we conducted in-depth interviews with 15 senior public sector executives working in information technology departments.

The structure of the study is as follows. First, we present the background of business models of public agencies, BMC and existing AI frameworks for public management. Then we present three main sections of the study as: (1) Design Science Research Methodology (DSRM); (2) Conceptual Development of PAIC; and (3) Empirical Validation of PAIC. Finally, we discuss the implications of the study, outline the contributions of the artifact, and highlight areas for future research.

5.5 Background

5.5.1 Business Models

Every organization has a business model, whether that model is explicitly articulated or not (Chesbrough, 2010; Teece, 2010). A well-articulated business model systematically describes how an organization creates and captures value (Chesbrough, 2007; Johnson & Lafley, 2010; Osterwalder & Pigneur, 2010). Business models have been defined as “the rationale and infrastructure of how an organization creates, delivers, and captures value” (Osterwalder & Pigneur, 2010). Business models have also been discussed as simplifying real systems to redesign an organization’s strategy for innovation opportunities (Osterwalder & Pigneur, 2010). Moreover, business models can also be used as a tool to redesign strategies for external and internal stakeholders of an organization (Massa et al., 2017). Business models play a crucial role in initiatives driven by innovation.

When new technologies (such as AI) are introduced, a viable business model is needed to ensure that the technology delivers value to the customer (Chesbrough & Rosenbloom, 2002). This often requires incumbent organizations to innovate their existing business models (Tongur & Engwall, 2014). Moreover, business models represent a new dimension of innovation that broadens the boundaries of innovation-related phenomena (Massa et al., 2017). Business model innovation is important as it, on the one hand, complements technology innovation and, on the other hand, is a form of innovation itself.

5.5.2 Business Model and Public Sector

While business models are most commonly used in the context of private organizations pursuing a commercial interest, their application has also been shown to be useful in other contexts, such as social services (Siebold, 2021), public interest (Feller et al., 2011), and sustainability (Pieroni et al., 2019). Few studies have applied the business model concept to the aspects of the public sector, such as e-government (Janssen et al., 2008), urban services in smart cities (Díaz-Díaz et al., 2017), ICT-supported citizen engagement (Panagiotopoulos et al., 2012), public service platforms (Ranerup et al., 2016), and mobile services in cities (Walravens, 2012). However, to date, researchers are yet to design and evaluate a business model tool that can be used by public agencies as they consider investment in AI systems.

The design of services is integral for the public sector to create public value (Lindgren et al., 2019; Twizeyimana & Andersson, 2019). Such a design should describe the objectives of public services, including relatively concrete outcomes (e.g., improved efficiency or improved services to citizens) as well as intangible outcomes, such as increased inclusion, democracy, transparency, and participation (Grimsley & Meehan, 2007; Twizeyimana & Andersson, 2019).

5.5.3 Business Model Canvas (BMC)

BMC is one of the most popular business model tools presented by Osterwalder and Pigneur (2010). It can be seen as the de facto industry standard for representing business models (Budler et al., 2021). BMC represents the core elements of a business model in a graphical template: customer segments, value propositions, customer relationships, channels, key activities, key resources, key partners, revenue streams, and cost structure (Osterwalder & Pigneur, 2010). The BMC is based on the Business Model Ontology (Osterwalder & Pigneur, 2010) which groups the components into four pillars: customer interface (segments, relationships and channels), product (value proposition), infrastructure management (activities, resources, and partners), and financial aspects (revenues and costs). As a canvas, the BMC visually presents the value-creation components, making it an effective tool (Bocken et al., 2014; Wallin et al., 2013).

Previous literature has examined business model innovation for technology adoption, such as the Internet of Things (IoT) in postal logistics (Fan & Zhou, 2011) and in drug supply chains (Liu & Jia, 2010). Dijkman et al. (2015) analyzed business models for IoT adoption using the perspective of BMC. According to this study, value proposition was considered the most crucial building block for businesses for IoT adoption. The second and third most discussed building blocks were customer relationships and key partnerships, respectively.

5.5.4 AI Frameworks for Public Management

Public sector–specific frameworks for AI deployment are limited (Zuiderwijk et al., 2021). A comprehensive framework by Wirtz and Müller (2018) outlines four layers to consider when deploying AI systems in the public sector: (1) AI applications and services layer; (2) AI functional layer; (3) AI technology infrastructure layer; and (4) public AI policy and regulation layer. Wirtz et al. (2020) present another AI governance framework that has five distinct layers: AI applications, AI challenges, AI regulation, public AI policy, and collaborative AI governance. The focus of this framework also emphasized the governance-related challenges of AI (Wirtz et al., 2020). While comprehensive and detailed, the existing AI frameworks are not tools such as the BMC that can be readily deployed by public sector practitioners. Moreover, these frameworks are theoretically grounded but, to the best of our knowledge, have yet to be put through empirical validation. Our research aims to fill these gaps.

5.6 Design Science Research Methodology (DSRM)

While "natural sciences and social sciences try to understand reality, design science attempts to create things that serve human purposes" (Simon, 1969, p. 55). DSRM is widely used in information systems (IS) research (Recker, 2012). In IS research, "design science creates and evaluates IT artifacts intended to solve organizational problems" (Hevner et al., 2004, p. 77). These artifacts can include constructs, models, methods, instantiations, technical, social, and information resources (Peffers et al., 2007).

This study uses guidelines of DSRM steps proposed by Peffers et al. (2007). According to Peffers et al. (2007), DSRM starts with: (1) identifying a problem; (2) defining the objectives of a solution; (3) designing the artifact; (4) demonstrating the artifact; (5) evaluating the effectiveness of artifact; and (6) communicating the artifact at relevant platforms as a solution to the problem formulated at the first step.

A problem is identified based on evidence and reasoning, and this process leads to defining a solution. The proposed solution is based on prior knowledge of the field. This knowledge helps in designing the solution, that is, the artifact. The following (fourth) step in the DSRM is to use the artifact to solve a predescribed problem, and thus demonstrate how the artifact is expected to work. The demonstration step in the DSRM is performed before evaluation. Evaluation is one of the most important steps in DSRM, and it reveals whether the artifact is a viable solution and can be communicated (Peffers et al., 2007).

DSRM is a suitable methodology for this study. According to scholars such as Hevner et al. (2004) and March and Smith (1995), design science research is fundamentally a problem-solving paradigm. It allows creation and designing of innovative artifacts that facilitate the problem domain through application and evaluation of the artifact. In this study, we used DSRM to design an artifact that can be applied and evaluated. AI deployment in the public sector is an emerging discipline. We deemed it appropriate to use DSRM to design and evaluate an artifact, as not many artifacts/frameworks or models are found in this discipline, to the best of our knowledge.

The development of PAIC follows a design science research methodology. There are various synergies between design science in information systems and qualitative research, such that both identify inductively emerging insights from data (Patton, 2022) and both can adapt to a flexible research design (Ritchie et al., 2013). More often, qualitative research methods have been proposed for validation or evaluation of the artifacts designed in DSRM (Kuechler et al., 2009). In this study, we deploy the qualitative method of expert interviews to evaluate PAIC. Interviews have been used in design science research to evaluate artifacts (Adomavicius et al., 2008; Hoch & Brad, 2020; Peffers et al., 2007). Using expert interviews to evaluate artifacts has been a common practice in DSRM (Offermann et al., 2009). We next present the problem identification and propose objectives of solution through DSRM. After that, we present the process of conceptual development of PAIC through various design iterations.

5.6.1 Identification of the Problem

While public agencies can learn from the private sector when it comes to designing and deploying AI systems, the contexts in which these two sectors operate are quite different (Berryhill et al., 2019). Private organizations pursue commercial motives (Rainey & Bozeman, 2000), whereas public agencies strive to create and maximize public value by deploying AI-enabled systems (Sharma et al., 2020).

Another major difference is the orientation of citizens in a public sector setting. Citizens have the right to know how and where their taxes are being used, what initiatives are taken for their economic prosperity, and how elected officials maintain social cohesion and development (Lepri et al., 2018a). Thus, public value covers a wide range of topics compared to customer value (Alford, 2002). In addition, the governance-related implications of AI have a far more sensitive impact in the public sector setting (Cath et al., 2018; Margetts & Dorobantu, 2019b; Sun & Medaglia, 2019).

We need to consider different contexts when deploying technologies in the public sector versus the private sector (Bozeman & Bretschneider, 1986). Considering AI requirements specific to the public sector, we explored the relevant literature and found little evidence for a structured approach to creating and delivering AI-enabled public value. We suggest that public agencies can benefit from support tools that take their unique value logic into account.

The role of AI in enhancing public value is undeniable; ubiquitous access of citizens to public agencies using 24/7 chatbots is just one example that shows that relying on human agents only would not have resulted in such fast and efficient services (Jain et al., 2018). However, the inherent opacity of algorithms can violate the basic principles of the citizens' right to know the criteria used for decision-making. Likewise, the tendency of algorithms to treat various social groups differently (owing to bias in data or algorithms) also outweighs the social objectives of equality. Similarly, access to citizens' personal data violates the principle of privacy, which is a fundamental right of citizens (Janssen & van den Hoven, 2015). By highlighting the interaction between social gains and the costs of deploying AI, we designed an artifact that covers AI issues, public value, and social guidance. This artifact is called the PAIC.

5.6.2 Objectives of the Solution

The solution to the problem identified in the previous step is to develop an artifact that depicts the AI-enabled public value. The literature review and identification of the gap indicate that BMC can be used as a starting point to identify the building blocks of AI-enabled public value creation. In addition, it presents a visual tool for understanding the value creation and capture process. The value logic of BMC makes it an appropriate tool for the value-creation process of any entity (profit or nonprofit) (Joyce & Paquin, 2016).

To position artifacts and their utility, different tools can be: (a) applied in different phases of designing and/or innovating BMs; (b) directed towards different stakeholder groups; (c) based on different units of analysis; and (d) used for measuring economic values and/or alternative values. As a solution to the problem identified above, we designed an artifact that is practically usable for designing or innovating business models according to the entity's values (Bouwman et al., 2020). The designed artifact is expected to: (a) outline the value logic of public agencies; (b) identify system-related components of AI for public value logic; and (c) assess the role of social components in creating public value logic.

5.7 Conceptual Development of Public AI Canvas (PAIC)

5.7.1 Design Iterations

To design PAIC, multiple rounds of iterations were informed by the literature and industry practices, and each iteration was followed by a discussion in the authors' team. Here, we present an overview of the various iterations that were performed before the final design.

Adaption and reconceptualization of the original BMC by Osterwalder and Pigneur (2010) for public agencies were made by using five design principles. The original BMC is described in a combination of nine building blocks. The building blocks of BMC are key partners, key resources, key activities, value propositions, customer segments, customer relationships, channels, cost structure, and revenue streams. In our first design iteration, a few building blocks were adapted and renamed according to the public sector context, such as customer relationships as citizen relationships. Similarly, cost structure and revenue stream were split into two components each. The first design iteration is the adaption of BMC from a private sector (commercial) to public sector (non-commercial) setting.

The adaption process shows the addition of two building blocks, that is, social cost and social value. It also renames three building blocks of the original BMC: key partners as key stakeholders, customer segments as citizen segments, and customer relationships as citizen relationships. The objective of this design is to go beyond economic costs and revenue streams and identify social issues related to AI adoption in the public sector. The study was presented at a leading information systems conference (reference held for blind review). In this iteration, the feedback we obtained from the scholarly community hinted at the addition of more components; hence, we sought another design iteration. The first design of the adapted BMC is illustrated in Figure 5-1.

Figure 5-1 *First Iteration of BMC*

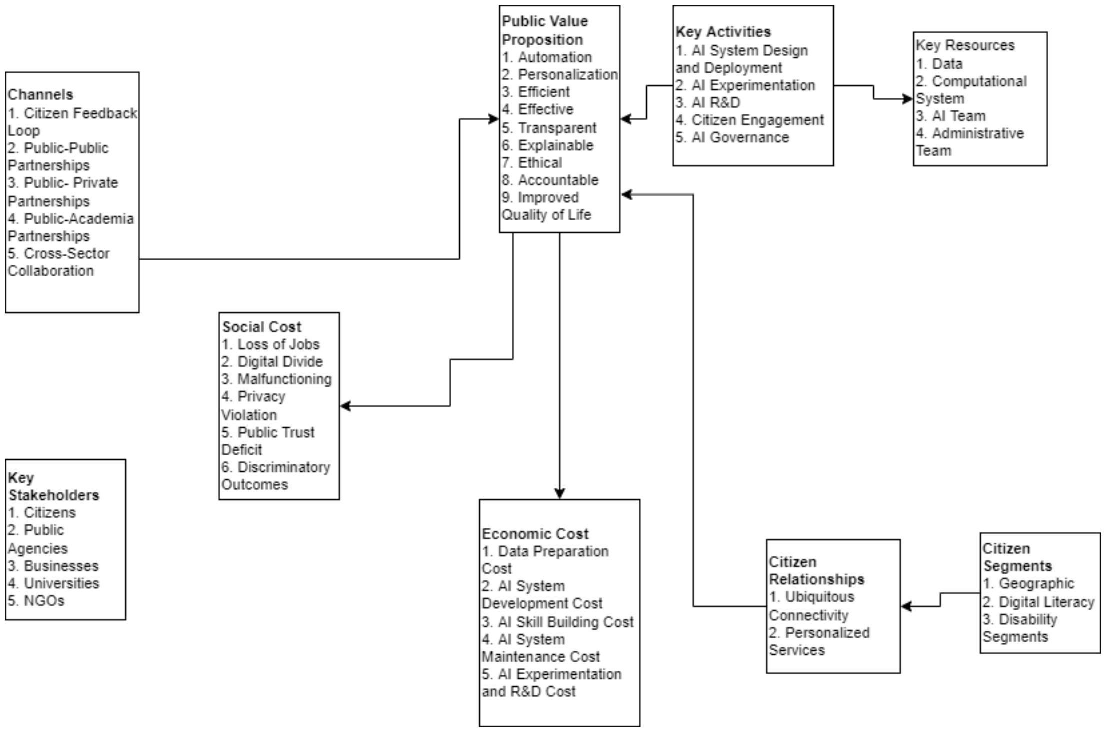
<table>
<tr><td colspan="3">Social cost</td><td colspan="3">Social value</td></tr>
<tr><td rowspan="2">Key stakeholders</td><td>Key activities</td><td colspan="2" rowspan="2">Value proposition</td><td>Citizen relationships</td><td rowspan="2">Citizen segments</td></tr>
<tr><td>Key resources</td><td>Channels</td></tr>
<tr><td colspan="3">Economic cost</td><td colspan="3">Economic value</td></tr>
</table>

The second iteration built two separate layers of canvas with the AI and public agency layers. Both layers contained the building blocks of the original BMC. On reflection, we noticed that this resulted in an extensive list of BMC components. For example, the AI layer has key stakeholders, such as data generators, data dealers, data scientists, system designers, system builders, IT managers, AI technology providers, AI R&D teams, AI ethicists, and AI regulators. The large number of components makes it redundant to present the value of artifact.

In the third iteration, to make the canvas output more meaningful, we designed a single-layer canvas with traditional BMC building blocks. The building blocks of original BMC are key partners, key resources, key activities, value propositions, customer segments, customer relationships, channels, cost structure, and revenue streams. In the third iteration (Figure 5-2), these nine building blocks were renamed for the public sector perspective, such as customer segments as citizen segments. When they were discussed among the authors' team, we found that each building block had a combination of technical, organizational, and social components. It was challenging to understand which components belonged to which building block. The single-layered BMC is shown in Figure 5-2.

To overcome the challenge of categorizing the building blocks found in the third iteration, we decided to design the canvas in three layers and relabel the building blocks in the respective layers. The final designed artifact named "Public AI Canvas (PAIC)," as shown in Figure 5-3, has three layers. We refer to the three layers as the public value-oriented AI-enablement layer, public value logic layer, and public value-oriented social guidance layer. This design of artifact (PAIC) was used for demonstration and evaluation. After evaluation, the artifact was named as the updated PAIC. We first define the three layers of the designed artifact (starting from the bottom AI-enablement layer), and then discuss its demonstration, evaluation, and communication according to the DSRM.

Figure 5-2 *Third Iteration of BMC*



5.7.2 Prevalidation PAIC Design

The objective of designing PAIC is to develop an artifact for public value-oriented AI deployment in the public sector. The three layers presented in PAIC revolve around creation and maximization of public value. The seminal work of Moore (1995) notes that public value creation was discussed in terms of government's role in society and deployment of practices to define public managers' roles. The public value literature suggests that "Public value has been described as a multi-dimensional construct—a reflection of collectively expressed, politically mediated preferences consumed by the citizenry—created not just through 'outcomes' but also through processes which may generate trust or fairness" (Alford & O'Flynn, 2008, p. 7). By drawing on the insights from literature on public value, we propose that public value creation through AI is not only an outcome but a process that requires value logic of public agencies at all three layers.

According to the public value paradigm, citizens collectively decide what they expect government to do for them via electing representatives. Through these collective preferences, government reflects such expectations when in action (Cordella & Bonina, 2012). Citizen expectations of government cover a wide variety of literature (Morgeson, 2013; Welch et al., 2005) and are not limited to citizens' behavior as customers who are interested in consuming the services of government. The collective values of society, such as safety, equality, fairness, justice, and sustainable use of public resources, form the overall concept of public value (Alford & Hughes, 2008; Alford & O'Flynn, 2009). To inculcate the logic of public value in whole process of AI deployment in public agencies, we develop PAIC grounded on public value concepts.

The three layers are: (1) public value-oriented AI-enablement; (2) public value logic; and (3) public value-oriented social guidance. These three layers reflect three major perspectives on the creation of AI-enabled public value. The artifact designed after multiple iterations (PAIC) that is subject to empirical validation is shown in Figure 5-3. Next, we will describe each layer in more detail.

5.7.2.1 Public Value-Oriented AI-Enablement Layer. This is the first (bottom) layer of the PAIC. The public value-oriented AI-enablement layer describes the technological foundations and prerequisites for deploying AI-enabled public services. We identified five components in this layer: (1) data; (2) algorithms; (3) AI capabilities; (4) public value proposition; and (5) economic viability.

5.7.2.1.1 Data. The first component of the AI-enablement layer is data that work as a fuel for AI systems. The best algorithms and AI cannot operate alone without data. Public agencies generate vast amounts of data and can benefit from this inbuilt resource if datasets are acquired and utilized proactively (Munné, 2016). The data component in the AI layer deals with public value-oriented data issues, such as data accessibility, cleaning, and securing storage for system development.

The role of data is integral to system development; any discrepancy in data quantity or quality can significantly impact system performance (A. Dey, 2016) and sabotage the objective of public value creation (Janssen & Kuk, 2016b). The data component in our artifact suggests that the business model of public agencies must outline all the steps required to prepare the data for AI systems.

Figure 5-3 *Designed Artifact: Public AI Canvas (PAIC)*

Public value-oriented social guidance layer

Social drivers	*Social objectives*	*Social viability (social costs)*		
• Digital excellence • Economic development • Improved quality of citizens’ life • Strategic competitiveness	• Automation • Sustainable Use of public resources • Improved Public services • Digital ranking	• Job losses • Privacy violation • Disparate treatment • Infringement of constitutional rights • Breach of public trust		
Public value logic layer				
Citizens and clients		*Key stakeholders*		
• Public value • Private value		• Public agencies • Public employees • Businesses • Universities • Technology companies • Nonprofits[2]		
Public value-oriented AI-enablement layer				
Data	*Algorithms*	*AI capabilities*	*Public value proposition*	*Economic viability*
• Accessibility • Cleaning • Secure Storage	• Bias • Transparency • Explainability • Accountability	• Technical • Human • Organizational	• Efficient • Effective • Transparent • Explainable • Ethical • Accountable	Cost–benefit analysis

5.7.2.1.2 Algorithms. Algorithms can cause an increase in bias, such as variable selection bias, confounding covariates, processing bias, and interpretation bias (Danks & London, 2017; Kordzadeh & Ghasemaghaei, 2021). Algorithms can also exhibit threats to public value logic, such as transparency, explainability, fairness, and accountability of AI systems (Janssen & Kuk, 2016b). The explainability of algorithmic output unfolds the logic used and adds to the public value (Zerilli et al., 2018). Therefore, PAIC proposes that regularizing algorithms for public value

[2] We thank one of the anonymous reviewers who suggested adding nonprofits as key stakeholders

propositions such as transparency, explainability, and accountability is unavoidable for public agencies.

5.7.2.1.3 AI Capabilities. The last component in the AI-enablement layer is the development of the AI capabilities according to public value logic. It includes technical, human, and organizational capabilities. This component suggests that institutional capacity to acquire, develop, and sustain AI capabilities must be in accordance with public value logic. For example, it highlights the need for public agencies to address the shortage of AI experts worldwide (Barrett & Greene, 2015) and devise strategies for hiring and retaining such talent. The PAIC must outline the technical, human, and organizational capabilities required for public value-oriented AI-enablement.

5.7.2.1.4 Public Value Proposition. The public value proposition is a set of value-oriented features of AI-enabled public services (Benington & Moore, 2010). For AI deployment in public agencies, we identified the following components.

- Efficient: The logical reasoning for adopting AI is to augment human capabilities and perform tasks with minimal resources. Fast public services create public value (Wirtz, Weyerer, & Geyer, 2019).
- Effective: AI-enabled public services must produce accurate, reliable, and intended outcomes for citizens and clients to enhance the effectiveness of public service design and delivery (Pencheva et al., 2020).
- Transparent: Opacity is an inherent feature of AI systems that makes the working of systems unclear. According to the value logic of public agencies, the delivery of AI-enabled public services must maintain adequate disclosure according to country- and agency-specific regulations (Alcaide Muñoz et al., 2017).
- Explainable: The explainability of AI-enabled systems suggests an understanding of system output. AI systems are criticized for their inherent opacity and incomprehensible interpretation of system output. Incidents of malfunctioning in AI systems create the need to make the output transparent and explainable (Brkan, 2019).
- Ethical: According to public value logic, AI systems must deliver fair and ethical output. Both ethics by design and ethics by regulation (Mittelstadt et al., 2016a) are outlined in the public value proposition.

- Accountable: The final feature of the value proposition of AI-enabled public services is accountability. PAIC proposes algorithmic accountability (Ananny & Crawford, 2018; Brkan, 2019) and human accountability (Koene et al., 2019) for AI-enabled systems' design and delivery.

5.7.2.1.5 Economic Viability. Revenue generation for public agencies comes from the central government's budget, public service fees, taxes, and fines (Marette & Crespi, 2005). Significant costs associated with the development of AI systems are system setup costs, AI skill-building costs, outsourcing of AI solutions, and cybersecurity costs. If an AI-enabled public service follows public value logic but is not economically viable, it cannot work longer. Therefore, the business model of public agencies must outline the financial costs and benefits associated with AI system enablement and deployment.

5.7.2.2 Public Value Logic Layer. The public value logic layer is the second layer of the PAIC. This layer describes the value logic of public agencies in the deployment of AI-enabled public services. It primarily focuses on the users of public services who are impacted by the deployment of AI-enabled systems. We identified two components in the public value logic layer: (1) citizens and clients; and (2) key stakeholders.

5.7.2.2.1 Citizens and Clients. In the PAIC, we defined two groups: citizens and clients. As is evident from this notion, citizens are members of the public who receive public value out of service. However, clients receive the private value of a public offering (Alford, 2002). For example, using self-service checkouts at airports would categorize foreigners as clients and not citizens.

5.7.2.2.2 Key Stakeholders. Agencies deal with various stakeholders (de Vries et al., 2018). Identifying key stakeholders is essential for actualizing AI-enabled initiatives (Sun & Medaglia, 2019). Based on a literature review (Hwabamungu et al., 2018; Sun & Medaglia, 2019; van Hulst & Yanow, 2016), we identified the following key stakeholders.

- Public agencies: Government agencies established under the law of a country that act as agents of the government.
- Public employees: Regular staff working in a public agency that is likely to be impacted by the deployment of AI.

- Businesses: The business sector of a country includes local companies, multinational companies, small and medium enterprises, start-ups, and public–private partnerships working within the geographic boundaries of a country.
- Universities: Higher education institutes of a country that have the right to award degrees.
- Technology companies: Technology companies are business entities engaged in developing technological products or solutions.
- Nonprofits: Nonprofit organizations are legal entities that are operated for a collective, public, or social benefit.

5.7.2.3 Public Value-oriented Social Guidance Layer. The social guidance layer is the third layer of the PAIC. This layer describes socially shared expectations associated with the deployment of AI-enabled public services. It covers the overall societal impacts of the AI-enabled systems. It considers the direct and indirect effects of AI on society. The societal impact of public value and vice versa was presented by Benington (2009), and we adapted the social guidance layer from these insights. The social guidance layer suggests that AI-enabled public value focuses attention not only on individual and current users of public services but also considers and protects the interest of nonusers and future users including next generations. We identified three components in this layer: (1) social drivers; (2) social objectives; and (3) social viability.

5.7.2.3.1 Social Drivers. Social drivers are long-term social goals that inspire an agency to contribute to countrywide social policies. These drivers motivate public agencies to achieve larger social objectives by employing AI technologies while creating public value. We identified four social drivers of AI deployment.

- The first social driver is digital excellence, which defines AI as a tool to create public value by increasing the use of technologies in society. Social drivers for AI indicate that technology is adopted by the public and not vice versa (Berryhill et al., 2019).
- The second social driver is economic development, which stands for an improvement in the economic well-being of society, communities, and individuals. The social guidance layer suggests that the efficiency obtained through use of AI systems to create public value must improve the economic well-being of society.

- The third social driver is improving the quality of citizens' lives, such as improving the physical, social, and mental well-being of society, communities, and individuals through use of AI technologies (Floridi et al., 2018b). Guided by social expectations, AI-enabled public value must improve the quality of life of users and nonusers of public services (e.g., use of native language chatbots to facilitate digitally less-literate communities).
- The fourth social driver is enhancing strategic competitiveness by increasing AI deployment (Cave & ÓhÉigeartaigh, 2018). According to the social guidance layer, the deployment of AI in public agencies must be driven by a country's overall ability to grow.

***5.7.2.3.2 Social Objectives*.** Social objectives are operationalized components of social drivers, which refer to breaking down social drivers into measurable terms. We derived four social objectives for public value by operationalizing the social drivers.

- The first social objective is automation. Automation allows a process or apparatus to work independently, with or without minimum human intervention, which improves the efficiency of public services (Smith et al., 2010). According to PAIC, this automation in public agencies must not only facilitate the service user (citizen) but also address the employment need of the employee (if automation dismissed their job).
- The second social objective is the sustainable use of public resources. This implies resource optimization of public goods and resources (Lepri et al., 2018a). For example, when AI deployment creates public value for current citizens, it must not deplete the resources for future generations.
- The third social objective is to improve public services for larger groups of the public and communities. For example, AI-augmented learning tools in education increase customized learning (Timms, 2016b), and real-time data-based traffic predictions can improve public transport (Kankanhalli et al., 2019).
- The fourth social objective is the digital ranking of public agencies or domains derived from the social driver of strategic competitiveness. According to PAIC, deployment of AI in public agencies must create public value and a high score in use of technologies. The high scores in use of technologies, for example,

index of information and communication technologies (ICT index) contribute towards the overall strategic competitiveness of the country.

5.7.2.3.3 Social Viability. The social cost of AI deployment is the cost incurred in any societal dimension as an outcome of the technological transformation. We defined five types of possible social costs.

- The first social cost is the loss of jobs. We recommend through PAIC that the business model of public agencies must consider the impact of automation on jobs.
- The second social cost is privacy violations. The use of citizens' data may violate their privacy. Therefore, the privacy of individuals and overall society must be maintained for the purpose of AI system design and deployment.
- The third social cost is the disparate treatment that may arise due to personalized public services (advanced services for digitally literate citizens and vice versa). The chance of a digital divide and socioeconomic disparity among various social classes are also likely to emerge, and thus PAIC suggests that business models of public agencies must be designed in a socially responsible manner.
- The fourth social cost is the infringement of constitutional rights, such as citizens' right to know about public resources.
- The fifth and final social cost is the breach of trust of users and nonusers of public services. Any malfunctioning in AI systems such as security breaches and evidence of biased outcomes (difference in the treatment of whites and nonwhites) can damage public trust in the public agency's credibility.

While there is always a possibility of incurring social costs, the concept of social viability suggests that social value must be higher than social costs.

5.7.3 BMC Adaptations for PAIC

The artifact is based on the BMC template; however, it has been adapted to the business models of public agencies. After a series of iterations, the artifact does not anymore depict the BMC and its building blocks exactly. The major changes are in relation to the overall structure of the BMC and changes to specific building blocks. First, the PAIC consists of three layers that reflect three major perspectives on the creation of AI-enabled public value.[3] Second, the adaptation of the BMC building blocks into PAIC is shown in Figure 5-4, with the labels and positions of the PAIC components in the block shown in italics.

The review of BMC shows that these building blocks are a combination of enablement capabilities (key resources and key activities), value creation (channels, customer segments, and customer relationships), and outcomes (cost and revenue). When these three broad categories of building blocks are adapted for public agencies for AI deployment, there are significant changes in defining new building blocks. For example, outcomes in public agencies are not primarily measured by financial profit (revenue minus cost) (G. A. Boyne, 2002). The value logic of public agencies is to create and maximize public value while maintaining economic viability. A customer-centric only approach in public agencies has been criticized as devaluing the concept of citizenship.

Figure 5-4 *PAIC Positioned in the BMC*

<table>
<tr><td rowspan="2">Key partners

(key stakeholders)</td><td>Key activities

(AI capabilities)</td><td rowspan="2" colspan="2">Value proposition

(public value proposition)</td><td>Customer relationships

(public value proposition)</td><td rowspan="2">Customer segments

(citizens and clients)</td></tr>
<tr><td>Key resources
(data, algorithms)</td><td>Channels
(public value proposition)</td></tr>
<tr><td colspan="3">Cost structure
social viability (cost)</td><td colspan="3">Revenue streams
(social drivers, social objectives)</td></tr>
</table>

Public agencies are not free to incorporate changes in doing business by only prioritizing users of their services; instead, such agencies should also adhere to the social guidance principles. Therefore, the public value logic layer in the designed artifact, PAIC, is related to social guidance. Similarly, building AI-enablement to create public value while considering social guidance is suggested by the PAIC. The final version of the PAIC is shown in Figure 5-3. Now, we will explain in detail the three layers of the PAIC.

[3] The concept of layers has been applied in previous AI frameworks for public management (Wirtz & Müller, 2018; Wirtz et al., 2020).

5.8 Empirical Validation of PAIC

The validation of PAIC took place in two steps. The first is demonstration of PAIC on a publicly available case, and the second is the empirical validation that took place through expert interviews.

5.8.1 Demonstration of PAIC

Before presenting the artifact for evaluation, we wanted to ensure that no critical component was missing. We selected one published case of AI deployment in the public sector to do so. This case was randomly selected from PPS (Partnership for Public Service, 2020). PPS is a nonprofit organization that aims to transform the way governments work. The cases published in PPS provide a holistic view of events. Although we made a random pick from cases of PPS to demonstrate PAIC, on investigation, we found this case reasonable to be used for the demonstration, due to several factors. First, the case is a recent example of AI deployment in the public sector. Second, the case offers various facets of information, for example, the name of the system, who initiated this project and who are the various partners, how the system works (technical information, etc.), and who the beneficiaries are of the system. Third, the case is published and easily accessible to public. Any of our readers can access and demonstrate PAIC. We used a mapping of the case to demonstrate the artifact (PAIC).

5.8.1.1 Case: AI-enabled Fire Prediction System—WIFIRE. The case used in this study to demonstrate the designed artifact is titled "Into the Storm: Using Artificial Intelligence to Improve California's Disaster Resilience," published in July 2020 (Partnership for Public Service, 2020). This case presents the use of an AI software called WIFIRE by the city and county of Los Angeles to make predictions about wildfires.

Previously, fire departments in California were using firefighters' insights and local climate conditions to predict the spread of fires. However, in 2015, the Fire Chief of the Los Angeles Fire Department (LAFD) used the University of California's WIFIRE, an AI-enabled online software developed by a university professor and students, to run real-time wildfire data. WIFIRE makes predictions using weather data such as air temperature, humidity, wind speed and direction, images from region's cameras, and satellite. It also uses soil images to determine the type of soil. The software then deploys predictive analytics and scientific models to predict fire patterns. The output of WIFIRE was proven to be more accurate and efficient than previous methods for predicting fires.

To further improve the performance of WIFIRE, in 2019 the Orange County Fire Authority engaged private tech companies. They launched a pilot program on another AI tool, the Fire Integrated Real-time Intelligence System (FIRIS). FIRIS validates the predictions of WIFIRE and uses infrared cameras and sensors to fly over wildfires. As the deployment of AI tools has played a role in disaster resilience, California’s federal, state, and local governments require improved access to quality data.

The mapping did not show any piece of information used in the WIFIRE development that was not covered by any of the three layers of the PAIC. Through these results, we observed saturation in the identification of the components. The mapping of the WIFIRE case on PAIC shows that all components, except economic and social viability, were found in this case. However, a greater focus on data components and key stakeholders was evident. The case study lacks information about the economic and social viability of the WIFIRE case. The mapping of the WIFIRE case on PAIC is shown in Appendix M.

5.8.2 Evaluation of PAIC

5.8.2.1 Expert Interviews. To evaluate PAIC, we examined guidelines by Peffers et al. (2012) and Hevner et al. (2004). Peffers et al. (2012) suggested expert evaluation as a viable artifact evaluation method. According to the DSRM, an artifact is evaluated based on the type of design, for example, whether it is a construct, model, method, or instantiation. The literature suggests that IS researchers have used qualitative methods to evaluate artifacts, compared with computer science researchers, who have used prototyping and more technical evaluation approaches (Peffers et al., 2012).

Peffers et al (2012) define expert evaluation as the assessment of an artifact by one or more experts. Similarly, Hevner et al. (2004) identified five perspectives to evaluate artifacts: observational, analytical, experimental, testing, and descriptive. They also suggested a rigorous artifact evaluation method that expresses the degree of freedom for designers and users. Based on the guidelines of Hevner et al. (2004), Leukel et al. (2014) analyzed the evaluation methods of design science research studies published in journals of the business and information systems engineering community. The results found expert evaluation to be a frequently used method in these studies. We opted for expert interviews as an evaluation method for the PAIC.

5.8.2.2 Interviewee Sample Selection. Our interviewees were IT personnel from public agencies working in managerial or higher roles. The interviews with practitioners were considered expert interviews, as suggested by Helfert et al (2012)Moreover, none of the interviewees had a related tenure of service less than five years. The five-year tenure of service was a threshold to recruit interviewees. The interviewees were initially contacted through LinkedIn, followed by emails for exchange of forms. The selection and recruitment of interviewees and conduct of interviews was performed after approval by the University Human Research Ethics Committee. The ethics approval number has been kept confidential to ensure a blind peer review process. (It can be furnished if required.) The application was approved in the category of negligible/low risk research involving human participants.

The interviewees' pool consisted of 15 participants from eight countries: Austria, Australia, Canada, Estonia, France, Italy, Spain, and the United States. The interviewees were selected from countries with use cases of AI system deployment in public agencies. The designations of the interviewees, including tenure of service and gender are shown in Table 5.1. The identity of interviewees would be disclosed if the country name were included in the demographics in Table 5.1.

Table 5.1 *Demographics of Interviewees*

ID	Designation	Tenure	Gender
1	Digital Delivery Lead: Local government	>10 Years	Male
2	IT Lead: Federal government	>10 Years	Female
3	City Manager: Digital initiatives	8–10 Years	Male
4	Technology Lead: City management	10 Years	Male
5	IT Director: Public agency	8–10 Years	Female
6	e-Governance Lead	>15 Years	Female
7	AI Initiatives Lead: Local government	> 10 Years	Female
8	Director: Agency for Policy and Service	8–10 Years	Male
9	Technology and Innovation Manager: State	>10 Years	Male
10	CEO IT Initiative: State	8–10 Years	Female
11	Director: Digital agency	8 Years	Male
12	Director: Public agency	10 Years	Female

13	Manager: Public agency	8–10 Years	Male
14	Director Data: Public agency	>15 Years	Male
15	Director IT: State	>10 Years	Male

5.8.2.3 Interview Protocol. We conducted semistructured interviews in two phases: the first phase consisted of a brief presentation by the interviewer about the designed artifact, and the second phase consisted of questions and answers. In design studies, it is imperative to first demonstrate the artifact before presenting it for evaluation (Hevner et al., 2004).We prepared an interview script to ensure that the designed artifact was understandable to the interviewees. We conducted five pilot interviews to test the quality of the interview protocol (Chenail, 2011). We found an early warning about one component of the social guidance layer during the trial-run interviews. As a result of the pilot testing, we updated our interview protocol to conduct interviews as envisioned. The interviewer ensured that artifact-related questions were covered. However, relevant topics of discussion were encouraged to capture more information. To validate during the interviews, the designed object was presented to the participants, and questions about the effectiveness of the artifact were asked. For example, we asked questions such as, "To what extent do you agree with the idea of having three layers in the PAIC?" In the next section, we present the details of the interview participants. According to the evaluation criteria, the set of exemplar questions is given in Appendix N.

On average, the interviews lasted for an hour, with 10 to 15 minutes spent on explaining the canvas. All the interviews were conducted using Zoom meetings, and most of them were recorded after formal approval was obtained in the interview consent form. After recording, the interviews were transcribed using the "transcribe" function of Microsoft Word.

The interviews were analysed using the deductive approach of coding, where an a priori template of codes was used. While using the deductive approach, a codebook is prepared for organizing the text (Fereday & Muir-Cochrane, 2006). In the codebook, the researcher defines codes before starting an in-depth analysis of the text(Crabtree & Miller, 1992). One code is data described in the codebook as "the degree to which interviewees agree or disagree with the effectiveness of the data component." In Appendix O, first order concepts, second order themes, and codes are described. For example, one first order concept is the scope of canvas layers, and one second order theme is the scope of the AI-enablement layer. The next section presents the various dimensions used for artifact evaluation.

5.8.2.4 Dimensions of PAIC Evaluation. The evaluation of the PAIC took place in three phases. First, the PAIC was evaluated as an overall artifact using the criteria suggested by Sonnenberg and vom Brocke (2012). Second, all artifact layers were validated through validated statements. Third, any updates in the artifact (canvas or layers) suggested by interviewees were addressed.

***5.8.2.4.1 Overall Artifact Evaluation*.** We used Sonnenberg and vom Brocke's (2012) method for the overall artifact evaluation. They identified five criteria for artifacts designed as models (Table 5.2).

Table 5.2 *Overall Artifact Evaluation Criteria*

Evaluation criteria	Description	Exemplar quotation (about overall canvas)
Completeness	Based on this evaluation criterion, an assessment is made as to whether the defined elements are complete. In other words, how do the experts assess the completeness and are there suggestions for expanding or reducing the model?	It's a good way of dividing up those things [three layers]. After creating the whole technical system [AI-enablement] and then discovering that you have a problem and finding who is responsible [public value and social guidance] for what. So that's very good that you already include all of those things there.
Fidelity with the real world	On the basis of this evaluation criterion, the conformity with reality in practice is assessed. In concrete terms, this means how well does the life cycle described by the experts fit with the elements we have defined?	It works as a good starting point to understand the process of AI adoption, as most countries have not yet started the journey of AI. For example, this will be most useful when several ways are all brought together to give us a bit of a kaleidoscopic view at first, until we learn how to really focus on these things [AI].
Internal consistency	This evaluation criterion is used to assess whether the elements are consistent. In other words, are the descriptions and definitions accurate, are the elements clearly defined, or are there overlaps; are the elements presented at the same level; what is the	It has a very clear logic because you have the technical area of the adoption process, the AI-enablement layer. And then, the top part is the social guidance. And in the middle, you have the public value logic layer, and I think it makes sense to me.

	size/scope of the elements? In addition, this evaluation criterion is also used to check whether and how the categorization and grouping of the elements fit.	
Level of detail	Based on this evaluation criterion, an assessment is made of how the level of detail is rated, that is, is the presentation of the elements at a sufficient level of granularity or should the elements be described in more detail/less detail?	I mean, it's brief. If you want to create something like this [presentation of PAIC], then keep it brief because otherwise you could go on forever to get an easily understandable sort of brief explanation; for that, I think it is good.

Table 5.2 (continued) Overall Artifact Evaluation Criteria

Evaluation criteria	Description	Exemplar quotation (about overall canvas)
Robustness	This evaluation criterion is used to assess how robust the model is in its entirety, that is, is the model as a whole questioned or confirmed? In addition, the model is robust if the elements are holistic from an expert's point of view, if the elements are consistent, and if reality can be well represented with the elements. Robustness is thus a "bracket evaluation criterion."	I would support this as a model. I think you can do [it in] a lot of different ways. I am watching organizations, community standards, and bodies all piece these together in a lot of different ways. I think this is a viable and valid way to do this. It's a nice simplification. I think the layered discussion is important.

Completeness. The interviewees agreed that the artifact was complete, in terms of covering the necessary components. As shown in the exemplar quotation (Table 5.2), the interviewee mentioned that the artifact covered technical, organizational, and social issues. The interviewee also liked the idea of having three distinct layers. One interviewee commented, "It strikes me as a valid and reasonably sensible way to look at the overall issue [AI deployment in public sector]."
The interviewees seemed not able to add any other layer to the canvas.

*Fidelity with the real world***.** When asked about the fidelity of canvas with the real world, interviewees agreed with the idea. However, for probing questions, such as, "How would you apply the canvas in your agency?", their responses varied. Some interviewees referred to the development of proxies or indicators to measure these components and apprehended that such proxies were not readily available and needed to be developed: *"Is there an indicator, a proxy or something that you could use for that* [application]*? Because this will definitely help you understand if there was any statistical data to apply."*

Internal consistency. The interviewees validated the internal consistency among the PAIC components. As shown in the exemplar quotation, the interviewee found it logical to have AI-enablement, public value logic, and social guidance layers. Overall, the interviewees seemed to agree with the logical connection between the elements. For example, one interviewee said, *"I am less concerned about time where it sits in a level as long as it's been considered, which layer it sits in necessarily, as long as it's kind of baked into the overarching kind of canvas."*

*Level of detail***.** When asked about the brevity of the information given on the canvas, interviewees liked the idea of keeping it brief, as shown in the exemplar quotation (Table 5.2). However, they suggested elaborating the elements and components in detail when publishing or using the artifact. As one interviewee said, *"I would think that there needs to be some verbiage in here—verbs to say what/how these are used, or what the context of those are."* During the first phase of the interview, bullet points were shown in the presentation of the canvas; the interviewees thus suggested to add descriptive details in the components that had been made in the manuscript.

Robustness. According to Sonnenberg and vom Brocke's (2012) criteria for artifact evaluation, the PAIC was validated by interviewees for completeness, fidelity with the real world, internal consistency, level of detail, and robustness. Asking about the robustness of the model was tricky, as most interviewees agreed to the idea of not having enough artifacts for the same reason and, thus, making comparisons was difficult. However, considering the artifact as one of its types, the interviewees mentioned it as a viable and reasonable artifact. As shown in the exemplar quotation, the interviewee mentioned using the components in many ways that highlight that the artifact can be adapted to various types and levels of AI adoption. Another interviewee suggested: "My main feedback is really related to that you have all the right components. It's how you're organizing them really will depend on who your audience is and why it's being used."

5.8.2.4.2 Evaluation of PAIC Layers. In the next section, we present each layer with exemplar quotations. A detailed codebook is provided in Appendix N.

Public value-oriented AI-enablement layer. Most interviewees' quotations endorsed the idea of the AI-enablement layer. One interviewee mentioned: "*I can't really think of anything else. To create the solution, you definitely need data obviously, and then you have to think about your algorithms for them … . I think it's really good that AI capabilities are included because this also often disregards this.*"

One interviewee highlighted fidelity with the real world by mentioning an example from Estonian e-governance systems: "*I know my colleagues who created the Estonian e-governance system. They always underline this, that they talk about enabling factors and so because a lot of people only then talk of technology and this is, that's actually, yes, the technology is there, of course. But the reason it's important is because that's what enables things, not just because of the technology.*"

The data component of the AI-enablement layer was validated by the interviewees. One exemplar quotation says, "*It's very important before you want to develop an AI solution that you would have clean and secure training data.*"

The algorithm component of the artifact was also endorsed by the interviewees. One respondent referred to the novelty of the concept: "*Yes, I think I couldn't think of anything else* [in algorithms components]. *Algorithm is still so new, so some authors I know claim that this is exaggerated. I'll just say that it is not well enough understood to say that it will be much worse than what people are now saying, so it definitely needs to be very much considered.*"

When asked about AI capabilities, interviewees appreciated the concept of combining technical, organizational, and human capabilities. As one interviewee mentioned: *"And if I start with the capabilities, I'm glad there that you don't just mention the technical, because one of the things that I see from working not just as I said on AI, but maybe on let's say how to use technology and governance."*

Public value propositions in PAIC were unanimously validated by all interviewees. One exemplar quotation depicts the endorsement as: *"And the public value proposition makes perfect sense. The way we kind of talk about it or the language that we use internally is about* [being] *simple, helpful, respectful, and transparent. What that does is it kind of describes the value in terms of what the citizen or client actually receives."*

Cost–benefit analysis is the last component of the public value-oriented AI-enablement layer. A few interviewees asked the interviewer probing questions about whether it is all about financial costs and revenues. Once they learned that this component covers only financial issues (quantitative costs and revenues), the interviewees validated the component. An exemplar quotation is presented here: *"In terms of the cost–benefit analysis, are you only thinking through from an economic viability perspective? You're thinking about the quantitative costs. The qualitative elements of why it would be better in terms of generating more value for the citizen client, is that correct? … That makes perfect sense."*

The evaluation process for the public value-oriented AI-enablement layer resulted in positive feedback. AI capability development was a highly iterated component of the AI-enablement layer.

Public value logic layer. The interviewees agreed to the concept of designing a public value logic layer in PAIC. By referring to the logic of public value creation and for whom these are for, one interviewee mentioned that: "*The public value logic makes perfect sense. I mean, if I have a machine that can do this, you know, and then I have another that can do this even faster, I would be asking them, so why I need to do this* [referring logic to use the machine]*?"* By mentioning the extent of detail of the public value logic layer, one interviewee said: "*I think those are fairly general enough that they capture the public value."*

Interviewees also validated two components of the layer, with citizens and clients as highly iterated components. One sample quotation for citizens and clients was: *"I think in terms of citizens and clients that makes perfect sense."*

The key stakeholders' group was also validated. Most of the interviewees appreciated the idea. For example, one interviewee showed excitement for identifying key stakeholders. One quotation says: *"One of the interesting things that you're doing here by creating this stakeholder community, it can give you a way of framing the considerations that each of these stakeholder groups may very well have in mind. How does this impact each of the participants in the group?"*

*Public value-oriented social guidance layer***.** The idea of the social guidance layer was validated by the interviewees. One interviewee said: *"*[Use of AI in the public sector] *Very important question—Is that what kind of effects can there be? It's likely to have any big impact on society or anything like that."* An interviewee from the healthcare sector emphasized the role of social and ethical implications of AI as follows: *"In terms of evaluating AI solutions, social acceptability of the results of the application of AI within healthcare are also important. Because AI might bring up issues and capabilities which have a social and ethical implications. Therefore, it's very useful to actually see the adoption process from both sides, definitely."*

The first component, social drivers, was found to be not valid during the pilot interviews. However, we included the component in a few initial interviews and found that it was not making enough sense to the interviewees. One type of feedback was about the difficulty in differentiating between social drivers and social objectives, while the other was about redundancies between subcomponents of social drivers, such as in the following quotation: *"It's not super clear to me how the two are different* [social drivers and social objectives] *and then I feel that I might be wrong, that digital excellence and high digital capabilities is a bit redundant."*

Considering the feedback of the pilot and a few real interviews, we updated the canvas wherein the social drivers' component was removed and a few of its components were made part of social objectives to see how interviewees responded. The feedback on social objectives was clear, and the interviewees validated the component. An exemplar quotation is as follows: *"You've got improved public services here, which is … which of course is a nice catchall and can include everything from education to law enforcement, to regulating, transportation and autonomous vehicles, to go to the Department of Agriculture, and so on."*

Social viability—particularly, the idea of breaking social costs and social values—was highly endorsed by the interviewees: *"I like the fact that indeed with AI, there is potential risks and costs and that you want to assess whether the benefits will outweigh the costs."*

The use of the phrase "potential social costs/risks" was also suggested by several interviewees, and we incorporated the word risks (potential social costs) after receiving repetitive feedback: for example, *"Social costs, again, for me, it's more risks and costs or potential costs. So, if I were you, I would introduce the idea of a risk somewhere."*

In the social guidance layer, social drivers were found to be nonvalidating, whereas social objectives were a highly validated component. Similarly, the interviewees validated social viability. However, several changes have been suggested in the social guidance layer. Among the three layers, the social guidance layer had the highest number of suggestions for improvement.

This section presented the validation of each layer and its corresponding components. The next section presents updates in the artifact suggested by the interviewees.

5.8.2.5 Updates in PAIC. We found the following themes from the interview data to bring updates in PAIC: a complete record of key insights drawn from interviews, and actions taken for the artifact updates, are shown in Table 5.3. This table presents the following themes: placement, graphical representation of layers and addition, deletion, reordering, rephrasing, and brevity of the components. Table 5.3 shows the key insights regarding the themes, exemplar quotations, and actions taken to update the canvas.

Table 5.3 *PAIC Updates*

Theme	**Key Insights**	**Exemplar Quotation**	**Action Taken**
Graphical Representation	All three layers are connected to each other.	1. *I would comment further on the interaction between these layers*	Three layers are connected to each other.
Brevity of Components	During PAIC presentation, bullet points were shown to which interviewees mentioned adding details.	1. *It's like more of a brief presentation but this is a great presentation, is nice and clear, but then if I'm really interested, I need to have an equally clear but the kind of a more detailed sort of explanation.*	Details about components have been given in the manuscript.
Addition of Components	AI-enablement Layer: 1. Integration	1. *The other thing I had in mind when talking about integration is that AI engines need to integrate with the existing technology ecosystem of the agency, will plug into, you know, into heaps of systems.*	Added in public value-oriented AI-enablement layer.
	Public Value Logic Layer: 1. Politicians/Political Support in Key Stakeholders 2. Regulators 3. Entrepreneurial Hubs	1. *If you want to add this, I just think about politicians because if you are in a public*	Added in public value-oriented AI-enablement layer.

		sector, politicians do play a role 2. *We need to think about this in the context of government as a regulator.* 3. *You may want to add something about like the entrepreneurial hubs in key stakeholders.*	
	Social Guidance Layer: 1. Safety (Objective) 2. Surveillance (Social Cost)	1. *I think that you have to put safety (in social objectives or viability)* 2. *I think that surveillance is a big one. We need to think about this.*	Added in public value-oriented social guidance layer
Removal of Components	AI Enablement Layer: (No component)	-	-
	Public Value Logic Layer: 1. Universities Are Not Key Stakeholders	1. *I know you have universities in there because you're in the university world.*	No action taken, as found only one confirming quotation.
	Social Guidance Layer: 1. Social Drivers 2. Strategic Competitiveness	1. *I guess it isn't clear to me what's the difference between social drivers and social objectives.* 2. *I would say that strategic competitiveness doesn't sound social. It's more like it's geopolitics.*	Removed from public value-oriented social guidance layer.
Reordering of Components	1. Move AI capabilities to public value logic layer. 2. Privacy violation and disparate treatment are parts of human and constitutional rights infringement.	1. *The* [AI] *capabilities to me comes into consideration actually in the logic layer.* 2. *It includes the privacy violation and disparate treatment are two subsets of the infringements.*	1. No action taken as found only one confirming quotation. 2. Action taken, as suggested.
Rephrasing of Components	1. Universities as academia	1. *We just call universities*	1. Five updates

	2. Data cleaning as data quality 3. Social costs also as social risks 4. Infringement of constitutional rights as infringement of human and constitutional rights 5. Job losses to be rephrased as opportunity cost.	*academia, though, because we pick up the broader view.* *2. Maybe clarification for data to the data quality is also very important.* *3. Social costs, again, for me, it's more risks and costs or potential costs, so if I was you, I would introduce the idea of a risk somewhere.* *4. I would say infringement of human and constitutional rights because human rights is sort of international.* *5. The opportunity cost that's driven by potentially freeing up* [human] *resources encounters what you are missing if doing this.*	(rephrasing) made in updated PAIC.

5.9 Findings: Postvalidation PAIC

This section presents the changes made in each layer and in the artifact.

5.9.1 Public Value-oriented AI-Enablement Layer

As a result of the validation process, few additions and rephrasing of the components were made to the public value-oriented AI-enablement layer. One of the most highly iterated additions is the integration of the AI system with the existing technological ecosystem of public agencies. We updated the public value-oriented AI-enablement layer, added system integration to AI capabilities, and rephrased data cleaning to improve data quality. The updated AI-enablement layer is shown below.

Table 5.4 *Revised Public Value-oriented AI Enablement Layer*

Public value-oriented AI-enablement layer				
Data	Algorithms	AI capabilities	Public value proposition	Economic viability
• Accessibility • Quality • Secure Storage	• Bias • Transparency • Explainability • Accountability	• Technical • Human • Organizational • System Integration	• Efficient • Effective • Transparent • Explainable • Ethical • Accountable	• Cost–benefit analysis

5.9.2 Public Value Logic Layer

The role of politicians and political support was highly mentioned by interviewees in the public value logic layer. Besides, the interviewees suggested that regulators and entrepreneurial hubs be added in key stakeholders. We rephrased universities to academia to broaden the scope of stakeholders (as indicated by the interviewees). Only one quotation referred to the addition of public agencies' mission to the value logic layer. No additions were made to the public value proposition for the components of economic viability. Based on comments from the interviewees, the updated version of the public value logic layer is shown below.

Table 5.5 *Revised Public Value Logic Layer*

Public value logic layer	
Citizens and clients	Key stakeholders
• Public value • Private value	• Public agencies • Employees • Businesses • Academia • Technology companies • Nonprofits • Entrepreneurial hubs • Politicians • Regulators

5.9.3 Public Value-Oriented Social Guidance Layer

The public value-oriented social guidance layer was found to be the most debatable layer in the canvas. In the additions section, a few additions were made by interviewees; however, a significant number of suggestions were to remove components. The findings showed that interviewees agreed with the idea of having a social guidance layer in the canvas; however, the interviewees were lacking in their understanding about social guidance components. The analysis of interviews showed that none of the interviewees agreed with the idea of categorizing strategic competitiveness as a social objective. Thus, we could not find evidence to include strategic competitiveness in the list of social objectives. Moreover, improved public services and quality of citizens' lives were deemed redundant. Therefore, improved quality of citizens' lives is included in the updated social guidance layer.

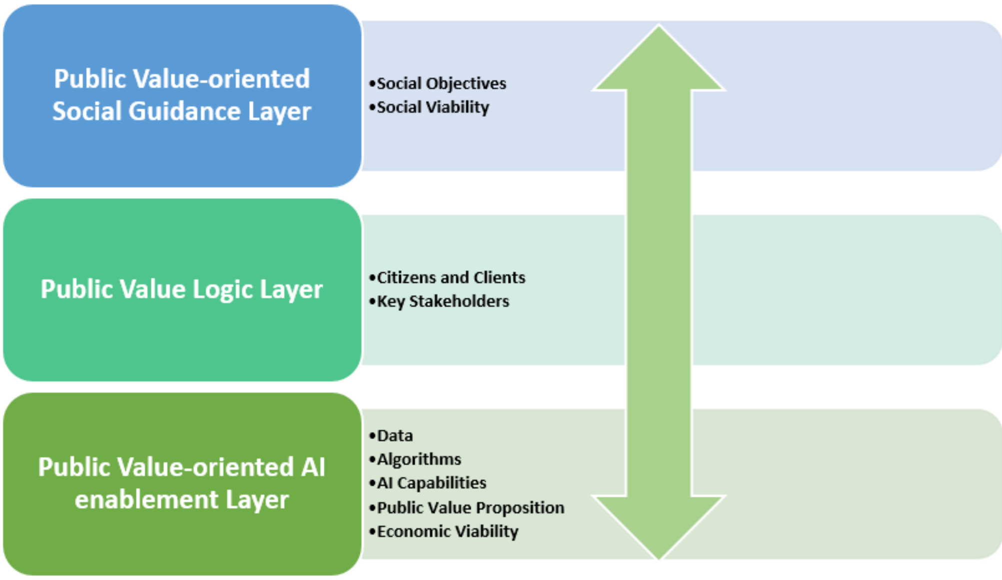
Table 5.6 *Revised Public Value-oriented Social Guidance Layer*

Public value-oriented social guidance layer	
Social objectives	Social viability (avoidance of potential social costs/risks)

• Economic development
• Sustainable use of public Resources
• Improved quality of citizens' life
• Citizens' safety
	• Infringement of human and constitutional rights
	    ○ Privacy violation
	    ○ Disparate treatment
	    ○ Surveillance
	• Opportunity cost
	• Breach of public trust

For social viability, the interviewees suggested using the phrase "potential social costs"; thus, we updated the social costs to potential social costs (risks). In addition, the interviewees suggested an extended phrase to use human and constitutional rights. We obtained insights about the different levels of components involved; for example, privacy violation and disparate treatment were regarded as subparts/subcomponents of infringement of human and constitutional rights. The opportunity cost that might occur in terms of loss of employment or infrastructural changes and breach of public trust because of the failure of any AI-enabled public service functions was validated by the majority of respondents. Based on the validation of the layers and updates suggested by the interviewees, the updated design of the PAIC is shown in Figure 5-5.

Figure 5-5 *Updated PAIC*



5.10 Discussion

This study designed an artifact based on the BMC template for AI deployment by public agencies. The designed artifact named PAIC was demonstrated on one public agency case, WIFIRE. When we found that PAIC covered the necessary components of the AI system deployment, it was then evaluated through expert interviews. As a result of the evaluation, few updates were made to the artifact. By integrating technical, public agency, and social issues into one artifact, the PAIC allows users to actualize AI by considering the design, development, and impact of AI deployment. The purpose of the PAIC is to enhance our understanding of the phenomenon of:

1. deploying new AI-based systems in public agencies where such systems have not been launched before. The objective of PAIC is to ensure that a public agency prepares for AI-enablement, creates and delivers value to the public, and considers the impact of such systems on overall society.
2. assessing how well existing AI-based systems create value for the public and positive impacts on society. The objective of PAIC is to evaluate and improve how a public agency implements AI-enablement, creates and delivers value to the public, and understands the impact of such systems on overall society.

When PAIC is compared with other frameworks, such as the four-layered framework by Wirtz and Müller (2018), it is evident that PAIC's public value-oriented AI-enablement layer summarizes the components of AI Technology Infrastructure

Layer and AI Functional Layer by Wirtz and Müller (2018). Although Wirtz and Müller’s (2018) framework offers extensive details about functionality and infrastructural support for AI deployment, public value orientation is not abundantly found in it. By integrating public value-orientation in all three layers, PAIC emphasizes deployment of AI for citizen-centricity and launches it at all three layers.

PAIC can advance public value. As defined by Alford and O’Flynn (2008), public value is preferences consumed by citizenry and is measured through outcomes and process. Merely producing preferences for citizens does not fulfill the meaning of public value. The processes or means used to generate these outcomes are also required to be true and fair. In PAIC, public value is generated through AI, thus process (AI-enablement) ensures public value-orientation and then public value logic (outcome), and social guidance (consequence) also follows public value-orientation.

The components list shown in PAIC also aligns with AI value considerations. For example, the public value-oriented AI-enablement layer in PAIC outlines data issues relating to data accessibility, maintenance, and secure storage. Similarly, for AI systems, unbiased, transparent, fair, explainable, and accountable algorithms lead to efficient, effective, transparent, ethical, explainable, and accountable public services and systems.

About generalizability of PAIC, it is pertinent to mention that although PAIC is focused on AI systems deployment in the public sector, there are certain components that can be used for related technologies or related contexts. For example, computing technologies such as IoT, Virtual Reality and Augmented Reality (VR/AR) can borrow components from the AI-enablement layer and social guidance layer. However, in the case of key stakeholders (from public value logic), the group of stakeholders would require some deletions and additions. Similarly, the first (AI) and last (social guidance) layers of PAIC can be transported to other nonprofit settings because social guidance and AI-enablement components are very likely to match.

When we compare the three PAIC layers with the BMC we see several changes. In relation to the AI-enablement, PAIC brings the specific technology (AI) and its main features in the canvas, as opposed to more generic key activities and resources in the BMC. Similarly, in the public value logic layer, PAIC differentiates between citizens and clients compared to citizen-only segments in the BMC. PAIC also lists a further division of value proposition, including transparent, ethical, and accountable public value that is a growing concern for AI-based systems. In the social guidance layer, PAIC also presents social viability that goes beyond numerical calculation of cost structure and revenue streams in BMC.

5.11 Conclusion

Following the DSRM, this study designs, demonstrates, and evaluates an artifact named the PAIC for AI deployment in public agencies. PAIC is another design iteration of an artifact that has already been presented at a leading IS conference (reference held for blind review). The first design was closely related to the original BMC template. However, the second design took a more holistic approach and covered the social aspects of public value. In this study, we defined public value-creation through AI by highlighting the difference between the value logic of private and public agencies.

This study shows that building AI readiness for public agencies is vital for AI deployment. The study used a DSRM to design, demonstrate, evaluate, and communicate the designed artifact based on the traditional BMC. The canvas was evaluated by conducting 15 interviews with IT managers of public agencies. All components, except one in the social guidance layer (social drivers), were validated by the interviewees. The findings indicate that PAIC covers most of the components of AI system deployment in public agencies. The PAIC offers various theoretical and practical contributions, as discussed in the next section.

5.11.1 Theoretical Contributions

Theoretical and conceptual guidance on how to create and capture public value with AI applications is scarce. Against this background, we derived a conceptual model, the PAIC, which guides public agencies for creating AI-enabled public value. The PAIC presents an application of the BMC (Osterwalder & Pigneur, 2010) for a specific type of organization (public agencies) and technology (AI). Our study makes three significant theoretical contributions to the literature.

First, we fill the gap in the literature regarding innovation in public agencies' business models for AI adoption in a socially responsible manner. To date, there is no known and validated approach for innovating the business models of public agencies by AI adoption that covers the technical, organizational (agency level), and social aspects of public value creation. With the PAIC, we contribute a carefully developed artifact for innovating the business models of public agencies for AI adoption.

Second, with PAIC, we introduce a theoretically founded and empirically evaluated artifact that constitutes a well-grounded foundation for further research in the field. By evaluating the artifact using 15 expert interviews, we present a robust tool that acknowledges AI's potential and associated risks in public agencies.

Third, this study contributes to digital innovation roles in design science research. Hevner et al. (2019) found that design science research could be a promising approach for exploring digital innovation. The contribution of this artifact is intended to be disseminated through publication in both peer-reviewed journals and practitioner forums, as the study encapsulates theoretical richness and practical usefulness.

5.11.2 Practical Contributions

Significant initiatives for AI deployment in public agencies are evident (Fatima et al., 2020b). However, such initiatives cannot create value for the public without developing AI readiness. Our study makes practical contributions to help AI deployment.

First, as a business model tool, PAIC can increase developers' problem-solving capacity and productivity, enabling them to address categories of problems that would otherwise be difficult to address (Thomke, 2006). It can also function as a "boundary object" between stakeholders, facilitating communication and collaboration regarding business model ideas (Bouwman et al., 2020).

In addition, with PAIC, we offer an artifact validated by practitioners in the field. By applying the three layers, nine components, and 36 elements of the PAIC, public agencies can help understand the dynamics of AI for public value-creation and evaluate how well their agency is deploying AI. Moreover, the PAIC offers public agencies a guiding tool for deploying AI in their agencies.

Using PAIC as a guiding tool can help public agencies address governance and regulatory requirements. For example, a fair and transparent AI system design would yield an algorithmic accountability mechanism (algorithms in the AI-enablement layer) by meeting regulators' expectations (key stakeholders in the public value logic layer) and protecting human and constitutional rights of citizens (social viability in the social guidance layer).

5.11.3 Limitations and Future Research

Despite presenting a novel artifact for public agencies' AI deployment, there are limitations to our study. First, the scope of this study is limited to the identification of various components such as data, algorithms, and public value propositions. This study does not suggest the operationalization of the components. In future research, operationalized indicators of components that can help measure and calculate the performance of public agencies can be devised; for example, how data cleaning/quality of an agency is measured.

Second, the study did not develop interactions between the various components in each layer. As it was first a type of artifact (PAIC), the scope of the study focused on identifying and validating the components of the three layers. It is more of a starting point to consider various dimensions—technical, public value, and social guidance—in public agencies' business models. Future research can explore associations between various components. Third, this study focuses on business model innovation. However, future research can ascertain the predictive value of business models in public agencies. The predictive value of AI-enabled business models would yield how successful the overall model is and determine which components are of key importance. Furthermore, the interconnectedness of public agencies' business models innovated for AI deployment can also be researched to facilitate mutual gains.

Future work can further develop PAIC as a visual tool for joint inquiry by developing and testing its visualization in terms of functionality, arrangement, and facilitation (Avdiji et al., 2020). Future studies can also extend the use of PAIC to other contexts. PAIC's public value logic and social guidance layers could be the starting point for developing a more generic business model canvas for public agencies. In addition, PAIC could be adapted, particularly the enablement layer, to deal with other new technologies in public agencies, such as blockchain, IoT, and VR/AR.

The designed PAIC can be used for AI system deployment in public agencies, which helps assess how well an agency has developed public value-oriented AI-enablement, how value logic of AI systems works in public agencies, and to what extent societal implications (public value-oriented social guidance layer) of AI-enabled systems have been maintained. The artifact offers various theoretical and practical contributions. However, the scope of this study is limited and acknowledges the need for future research.

Chapter 6: Discussion and Conclusion

While much has been discussed about the affordance of technology artefacts, this thesis focuses on AI's potential and actual affordances for the public sector. This thesis, aimed to add to the body of knowledge on AI affordances for the public sector using the lens of affordance theory. The findings represent new knowledge derived from a range of methodological approaches used to answer the core research question of how AI affordance is perceived and actualised across countries in the public sector. Drawing on the affordance theory this thesis investigated the potential and actual affordances of AI for countries in the context of the public sector by addressing the following three sub-questions:

1. What are the AI affordance perceptions across the nations?
2. 2A: What have been the underlying socio-political factors that have caused differences between AI affordance perception and actualisation among countries?

   2B: Why have the underlying socio-political factors caused differences between AI affordance perception and actualisation among countries?
3. How can AI affordance be actualised to create public value?

The thesis used various research methodologies involving qualitative research, mixed-methods research, and design science research to explore the overarching and subsequent research questions. This thesis has plenty of theoretical and practical contributions to the body of knowledge.

6.1 Research Synthesis of the Studies

This section presents the integration of key findings and implications of the studies in the thesis. The thesis began with a problem statement of AI affordances and actualization for the public sector due to variations in various socio-political factors of countries. It identified gaps in the literature on AI affordances and the lack of tools to actualize AI in the context of public sector. The thesis then postulated the use of affordance theory to explore the perception and actualization of AI as affordance theory outlines the possible benefits of an artefact, which have not been fully identified. Three research questions were answered through three studies to explore the phenomenon of AI affordance perception and actualization.

The thesis began the investigation of national strategic AI plans of countries. The release of national strategic AI plans shows the strategic planning of governments. The literature has suggested three critical drivers of strategic planning in the public sector: 1) bringing relevant stakeholders on one platform; 2) developing strategic thinking and acting plan; and 3) identifying critical priorities for future action (Bryson & Roering, 1988). The use of an affordance lens allowed the viewing of affordances that have been considered important in the national plans. Thus, the first study (see Chapter 3) analyses the national AI plans of countries to understand the perception of AI affordances that is prevalent among various countries.

The findings of the first study indicated that not every national AI plan releasing country perceived the same affordances of AI. It also signalled that each country's perception of AI affordances was determined by several factors that needed further investigation. Another study was conducted to determine what factors impacted on the perception and planning for AI affordance actualisation. Study 2 of the thesis (see Chapter 4) focused on identifying contextual factors that impacted on the actualisation of AI affordance.

Study 3 centred on AI affordance actualisation in the public sector, and two reasons for emphasizing the public sector were emphasised. First, AI actualisation was viewed from operationalised units of the government structure, that is, public agencies. Second, the findings of both Studies 1 and 2 highlighted AI deployment in the public sector as a core goal for AI deployment. Following the design science research approach, Study 3 focused on devising AI actualisation artefacts in the public sector.

6.1.1 Key Findings and Implications of Study 1

By answering the first sub-research question that examined the AI affordance perceptions across nations, the research highlighted that the future of the public sector is rooted in AI. The first sub-research question was answered through Study 1 titled

“Fatima, S., Desouza, K. C., & Dawson, G. S. (2020). National strategic artificial intelligence plans: A multi-dimensional analysis. Economic Analysis and Policy, 67, 178–194. https://doi.org/10.1016/j.eap.2020.07.008”. In the thesis, this publication is presented in Chapter 3: Study 1- AI Policy Analysis

Study 1 builds on the narrative that the race of our time is the quest for domination in artificial intelligence. As a result, countries worldwide have been investing significant resources to build and mature their AI capabilities. They have also been crafting national strategic plans about how and where to invest in AI. Taken together, these plans provide a snapshot of the global state of AI investments and how national governments have been thinking about how to utilize their resources best. By studying 34 AI strategic plans of more than 1,700 pages, study 1 found that governments failed to plan for operational investments, continued to be far more aspirational than practical in their planning, and failed to consider funding realities. Generally, the plans examined public sector functions and sectors of the economy that could benefit from AI, how to build AI capacity, governance concerns, data management opportunities and challenges, and algorithmic design challenges.

The plans revealed that countries around the world saw similar opportunities in AI. Plans most often emphasized health care, technology, agriculture, and manufacturing as the sectors with the most incredible opportunity to transform AI. Countries understood the potential of this technology to retain and possibly advance their competitive positions in core industries.

The plans also revealed similar conceptions of risk. They often examined how to develop regulatory frameworks for AI systems (e.g., when they fail), the impact of algorithms on social inequality, and the need to increase the transparency associated with AI systems. Given that AI systems must be built to deliver public value, addressing how these systems might go astray. It was found that most plans lacked critical elements. These missing components had to do with the how, that is, how national governments were going to mobilize their nations on the AI journey.

Despite these efforts to blueprint an AI future, the plans generally lacked sufficient (or any) detail on their execution, including who would be responsible and under what timeframe these objectives would be achieved. They also omitted metrics to gauge performance. Ideally, one or more agencies could lead the charge on various initiatives. In addition, the plans could ideally specify the coordination standards between federal, state, and local governments.

The plans also tended to ignore funding realities. Technologies, such as autonomous vehicles, are likely to significantly impact local government revenues, consider the drop in income from speeding tickets, for example, but the plans failed to acknowledge how AI will affect public finances. AI systems will impact the very nature of public finances regarding how taxes are levied, social security is provisioned, and public infrastructure is funded.

For nations to prepare themselves for AI, the public sector must drive the conversation on how AI will impact its regions, cities, and communities. However, none of these plans had an associated communication strategy. Beyond having the plans posted on websites, there was little detail on how governments planned to communicate with their constituencies on the implications, next steps, and opportunities for engagement.

6.1.2 Key Findings and Implications of Study 2

The second research question that was broke down into two sub parts examined what and why underlying socio-political factors caused differences between AI affordance perception and actualisation among countries. “is answered through publication titled “Fatima, S., Desouza, K. C., Denford, J. S., & Dawson, G. S. (2021). What explains governments interest in artificial intelligence? A signalling theory approach. Economic Analysis and Policy, 71, 238–254. https://doi.org/10.1016/j.eap.2021.05.001”. In the thesis, this publication is presented in Chapter 5: Study 2- Exploration of AI Interests.

Study 2 presents decoding the signals transmitted through the national AI plans. These national AI plans provide information about the intended use of AI within each country and what this information signals about countries' priorities for AI. For example, some plans mentioned AI for weaponisation while others condemned AI-enabled wars; some captured details on an ethical framework design while others gave few or no clues about how AI governance was ensured.

The ability to correctly interpret these signals is helpful for various internal and external stakeholders, such as citizens, non-government organisations (e.g., OECD, UN), other countries, and policy analysts to predict the future trajectories of AI. For example, India’s AI plan signalled concern for public consent by mentioning“upon proper and informed consent from the citizens, these anonymized data may be shared for artificial intelligence and data analytics” (India AI Plan, 2018). Similarly, France’s AI Plans emphasised ethics by design, by “looking beyond engineer training, ethical considerations must be fully factored into the development of artificial intelligence algorithms” (France AI Plan, 2018).

However, not all signals are created equally, and signals can vary in intention and trustworthiness. This is similar to buying a used car: The seller may say that a car is highly reliable but then offers a price far below market value. This non-intentional (inadvertent) signal suggests that there may be a problem with the car that is not disclosed. Similarly, the used car seller may say that the car is highly reliable but then refuses to give any mechanical warranty on the car, evidence that the signal is not trustworthy.

Signals can be illuminating in understanding the fundamental drive for AI development. In much the same way, the signals in national AI plans require interpretation. Correctly interpreting signals allows the reader to understand the country’s motivations, such as why certain countries plan on weaponisation or some are more concerned with the ethics of AI. According to signalling theory, four types of signals were evaluated against the plans, that is, 1) traditional signals, 2) inadvertent disclosure signals, 3) opportunistic signals and 4) mixed signals.

The results indicated that bolstering AI research and access to data required for AI system development were the most widely accepted outcomes. The group of countries releasing AI plans showed that building capabilities for AI research and data accessibility are necessary preconditions to achieve the other outcomes. Algorithmic ethics and AI governance showed variety across countries. Democratic countries led authoritarian countries in addressing problems around algorithmic ethics and governance.

However, among democratic countries, those with an immature technical environment were more likely to address ethics and governance than those with a mature technical environment. These countries included New Zealand, India, Lithuania, Spain, Serbia, Czech Republic, Mexico, Italy and Uruguay. These findings also indicated that countries that lagged technically in this area focused on ethics and governance not just because they were behind but also because they put in the legal framework to defend against the external use of AI and shape the direction of their internal developments. This strategy, while admirable, may slow the spread of AI from other countries that are not as aware of ethical and governance considerations. Finally, the results indicated that despite asserting an interest in using AI for public services, some countries lacked supporting contextual factors such as political, social and economic conditions. This casts doubt on the validity of the oft-stated objective that adopting AI at the national level improves citizens' quality of life.

The next step performed in the study was to interpret and assess the statements in the plans based on their intentionality (did they mean to say something?) and their veracity (was what they said supported by other evidence?). Based on the results of the analysis, an intentionality and veracity matrix of five outcomes was prepared. The first two outcomes, AI research and data, were placed in the deliberate and high veracity quadrant. Countries that expressed the intention to develop both the capabilities and the generation of these outcomes were also validated by the contextual conditions. If the information in the AI plans aligned with contextual conditions, it was referred to as validated information.

Similarly, the contextual conditions also validated algorithmic ethics and AI governance. However, the intention of the information was not deliberate (not expressed in the plans but found in contextual conditions). Democratic countries deliberately discussed the use of AI in public services. However, the information was not validated by contextual conditions and, thus, was placed in the deliberate intention and low veracity quadrant. The authoritarian countries' intentions to use AI were inadvertently depicted but the veracity of information was low and thus categorised in the last matrix (inadvertent and low veracity signals).

The advancement of technology has changed the geopolitics of AI for countries around the globe. The national AI plans of countries presented sophisticated goals for building AI competitiveness; however, there was significant variation between intentional claims and veracity checks of these plans taken through the consultation of contextual conditions.

6.1.3 Key Findings and Implications of Study 3

The third research question "How can AI affordance be actualised to create public value?" was answered through Study 3: *"Fatima, S., Desouza, K.C., Buck, C., Fielt, E. (2022). Public AI Canvas for AI*-Enabled Public Value: A Design Science Approach, Government Information Quarterly". In the thesis, this study is presented in Chapter 5: Design and Evaluation of Public AI canvas.

This study conceptualises Peffers' et al. (2007) design science research methodology to design an artefact grounded on the traditional business model canvas (BMC) for AI deployment in the context of the public sector. The study aimed to find AI affordance actualisation tools for the public sector. A review of the relevant literature showed that business models define the rationale through which organisations create, deliver and capture value. The literature also showed that innovation-led phenomena, such as the adoption of new technologies, also require business models to adapt according to this change.

A deep understanding of relevant literature depicted that the adoption of emerging technologies, such as AI, has been far more common in private than in public sector organisations. Due to the fast-paced adoption of AI in the private sector, there has been a greater trend of finding AI deployment tools in theory and practice, such as AI adoption through the unified theory of acceptance and the use of technology (UTAUT) (Venkatesh, 2022) and AI adoption at the firm level through the technology organisations' environment framework (AlSheibani et al., 2018). There have been limited frameworks for AI deployment in the public sector (Wirtz, Weyerer, & Geyer, 2019; Wirtz & Müller, 2018; Zuiderwijk et al., 2021). Study 3 designed an artefact that could facilitate AI affordances actualisation for the public sector in order to address this gap.

Design science research methodology was used in Study 3. The methodology presented by Peffers et al. (2007) was adapted following Gregor and Hevner's (2013) publication schema. The role of business models in technology adoption was discussed, and innovation in business models has been considered a reasonable way to deploy AI technologies. From the literature review on business models, the business model canvas (BMC) was found popular among the scholarly community. Also, BMC is a useful visual tool to depict the value logic of an entity. After identifying the difference between the value logic of private and public organisations, it was postulated that public sector organisations lack frameworks to deploy AI technologies.

After several iterations in the artefact's design, a final design was made, named PAIC, containing three layers. The concept of adding three layers was grounded on relevant AI frameworks introduced by Wirtz and Muller (2018) and Wirtz et al. (2019). The three layers of PAIC that have common attribute of public value orientation are: 1) AI enablement; 2) public value logic; and 3) social guidance. According to DSRM, the next step was to demonstrate the designed artefact using an existing case. An AI-enabled disaster resilience system called WIFIRE was used to demonstrate the artefact. This case selection was made to closely observe the WIFIRE's societal dimensions of the AI-enabled system.

This case offered greater details than other available cases because the demonstration of the artefact used a secondary source of data to map the artefact. The case provided information about key stakeholders, users, and communities affected by the system. It also extended details on types of data used for designing the system.

To evaluate the artefact, interviews of experts involving public IT managers were conducted. The findings of the interviews indicated that among the three layers of the PAIC, interviewees talked about the AI enablement layer the most. The second most discussed layer was the public value logic layer, while the third layer, social guidance, was found to be least discussed. A more significant number of updates were made in the social guidance layer. It can be implied that interviewees had greater exposure to AI enablement components, such as accessing data and preparing it for system processing. There were more affirmatory interview quotes about building AI capabilities. In the public value logic layer, few updates were suggested by interviewees such as regulators as critical stakeholders.

Interviewees suggested significant updates in the social guidance layer and mentioned that social objectives and social drivers did not seem distinctive. The reason for presenting social drivers and social objectives separately was to explore the purpose of deploying AI in public sector agencies. For example, is the economic development of society instigate the need to deploy AI-based systems? The social objective was presented as a means to satisfy the social driver; for example, the sustainable use of public resources could contribute to the economic development of society. The two components were merged as social objectives after recurring overlapping responses between social drivers and social objectives. This implies that social guidance related to AI deployment is still in its early days. The focus of AI deployment initiatives was mainly on building the capabilities. The suggested approach for successful AI deployment is to consider social issues alongside capability development.

6.2 Synthesis of Thesis Results

The exploration in this thesis of AI affordances for countries in the context of the public sector started with an analysis of the national strategic AI plans of countries.

The boost of AI potential for countries has gained momentum since 2015. However, the release of national strategic AI plans by countries has increased the pace of AI deployment and exhibited substantial efforts to integrate the whole process of AI deployment at the national level. Before this, there were extensive investments, such as extensive budget allocations, for AI research and development (Castro et al., 2019; Davenport, 2019, 2019; Hao, 2019b; Waters & Lucas, 2018), increasing competition for AI talent acquisition (Cyranoski, 2018), and increasing collaboration among countries to advance AI research (O'Meara, 2019) are some of the instances that signalled the magnitude of AI initiatives across countries.

This thesis explored how various countries perceived and actualised AI affordance. The initial investigation began with identifying the countries that had released national AI plans. Among the total of 195 countries in the world (Worldometer, 2021b), 34 had released national strategic AI plans up to January 2020. The surprisingly low percentage (less than 20%) of the world's countries that have formalized AI through a policy statement led to further investigation. Examining the list of these 34 countries, the assumption could be that these countries share attributes that grouped them. The shared attributes could be the size of the economy, technology advancement level, population size, geographic proximities, the need for national security, high digital literacy, or the type of economy. However, the findings differed from expectations, because among these 34 countries, there were countries with small economies, for example, Malta ($ 12.52 billion GDP) (Worldometer, 2021a).

Similarly, Luxembourg was also found in the list with a small population size of 613, 894. Upon further exploration, it was found that not all countries needed to developAI for national security; for example, few European countries were not predictably in a geographic location to build AI for military threats or national security. Furthermore, not all listed countries had digital economies; for example, India has a rural economy (Chand et al., 2017) and aimed to formalise AI through a national plan. The variety among country profiles led to the proposition that the drivers behind formalising AI affordances were multifaceted and could not be attributed to one factor. National strategic AI plans were analysed and presented in Study 2 (see Chapter 4) to explore these propositions.

This study helped in gaining insights about the perception of AI affordance among countries. The analysis of national strategic AI plans identified six common themes: use of AI in the public sector and industries; AI data and algorithms; capacity development and governance of AI. For example, France's AI plan referred to inculcating the spirit of algorithmic ethics in system designers and developers:

> … research staff, engineers and business owners who contribute to designing, developing and marketing AI systems play a decisive role in tomorrow's digital society, so it is vital that they act responsibly and factor in the socio-economic effects of their actions. With this in mind, it is important to make them aware of the ethical issues involved in the development of digital technologies right from the start of their training. (France AI Plan, 2018, p. 15).

This quote from France's AI plan shows that it intended to take advantage of the AI affordance potential while protecting the interest in socio-economic factors. Similarly, Australia's AI plan emphasised AI for healthcare and aged care as the number one priority (Australia AI Plan, 2019, p. 34). There are numerous examples discussed in Chapter 3. The take-away from these plans' analysis is that the tendency to prioritise AI affordances was not shared across countries. This finding led to the further investigation of why these priorities differed and the identification of factors that drove such differences.

After identifying AI affordance perception among various countries, the investigation of underlying reasons came next. The perception about AI affordances was driven by the intended outcomes that countries waned to achieve According to affordance theory, the intended outcomes of the user determine the potential use of technology (Anderson & Robey, 2017). Thus, Study 2 (see Chapter 5) focused on the causal recipes of various technical, economic, social, and political factors (called contextual conditions) with the intended use of AI. To understand the message conveyed by AI plans, signalling theory was used. According to signalling theory, one entity attempts to convey important information to induce the other party to make a favourable choice (Spence, 1978).

Through the deployment of signalling theory, interesting insights appeared between the contextual conditions and signals emitted through AI plans. For example, countries' tendencies to signal information that could impact on them favourably, for example, AI research or data, were found in the traditional signals matrix, which means that countries were not reluctant to filter such information. This information is advantageous for countries to gain the attention of stakeholders, such as investment opportunities or research collaboration. However, not all kinds of information were presented the same way. Using signalling theory, such non-agreements between claims in the plans and contextual conditions were found. Study 2 listed such signals as opportunistic and mixed signals because signal fit, signal consistency, or signal reliability were not validated using fuzzy set qualitative comparative analysis.

Despite the claims made in AI plans, one way to investigate the veracity of such information is through the agreement between AI plans and contextual conditions. The findings of Study 2 suggested that contextual conditions can determine AI affordance actualisation. The findings suggested discrepancies between both sources of information using signal fit, consistency and reliability. However, it was vital to investigate whether such non-alignment was deliberate or non-deliberate. Study 2 explored the "why" of AI affordance perception and signalled the actualisation of AI affordance in a socially viable manner.

The core objective of deploying AI in the public sector is to create and maximise public value. For AI affordance actualisation, public agencies must be ready to actualise the potential of AI. Study 3, therefore, suggested changes in the business model of public agencies to adopt AI in a technically and socially viable manner with the maximisation of public value.

Any discrepancy in AI-enabled systems without AI enablement can damage public value creation. For example, the AI-enabled Canadian government's payroll system, Phoenix, failed to make salary payments to public sector employees and cost $2 billion CAD through wrong and delayed payments. According to investigations, Phoenix could not handle the complexity of the federal payroll system as it had not undergone the required number of iterations to be deployed on a large scale. The Ottawa administration had suggested pilot testing "against the real complexity of federal government HR and pay needs" of the new payroll system in Canada (Charette, 2018).

This is one of the examples where the use of AI sabotaged the objective of public value. Therefore, Study 3 suggested three distinctive layers in the business models of public agencies: public value-oriented AI enablement; public value logic; and public value oriented social guidance layer. The three studies connect to understand the phenomenon of AI affordance perception to actualisation in the public sector. The findings of Study 3 indicated that there was greater awareness about enabling the capabilities of AI than of the social issues related to AI deployment in the public sector context.

6.2.1 Integrated View of AI for the Public Sector

The overall situation of AI in the public sector context presents a complex phenomenon. This thesis contributes to the overall discipline in several ways. First, there are diverse definitions of AI For example, UNESCO (2020) defined AI as a system of algorithms and models that can plan, predict, and control tasks whereas, in technical domains, such as computing and design, AI has been defined as various technologies (machine learning, neural networks, fuzzy logic, natural language processing, cognitive mapping and cyber-physical systems (Zuiderwijk et al., 2021). This thesis builds on a broader definition of AI, that is, systems that exhibit human-like intelligence are AI-enabled systems (Wirtz, Weyerer, & Geyer, 2019). Due to the breadth in defining the scope of AI systems, it remains an extensive and multidisciplinary research field.

The three broader types of AI literature in the public sector present various topics and signal the need to combine them for a holistic understanding of the phenomenon. Second, as identified in the research gaps, one stream of scholarly studies focused on governance-related issues of AI, such as data privacy (Janssen & van den Hoven, 2015), safety (Srivastava et al., 2017), risks (Toll et al., 2020) ethical dilemmas (Mittelstadt et al., 2016a), regulatory frameworks (Bayamlıoğlu & Leenes, 2018), and accountability in algorithms (Busuioc, 2020). Another stream of public sector literature has focused on building the organisational capabilities to deploy AI systems (e.g., AI readiness, data curation- algorithm biases). The last broad set of literature has presented public value creation through AI-based systems, such as increased efficiency, better performance, task automation, and better quality of life. This thesis combined topics of AI governance, AI readiness and AI-enabled public value creation. Keeping in view the broad range of AI topics in the public sector, this thesis suggests the use of hybrid (multidisciplinary research areas) academic and practitioner outputs to contribute to the overall discipline.

Third, the literature on AI for the public sector presents the pros and cons of AI, for example, scholarly studies on the AI advantages (Mikalef et al., 2021b) and AI challenges and risks (Mikalef et al., 2019). In this thesis the affordance lens to view

AI's potential for the public sector is used, which suggests the possible benefits of AI that the goal-oriented user can achieve, which are achieved by discarding the disadvantages in the first place. The affordances of AI discussed in this thesis are net of AI pros and cons, that is, Study 1 identified AI advantages and risks; similarly, Study 3 focused on governance-related issues (social guidance layer) and public value gains (public value logic layer) in one artefact. Therefore, this thesis contributes to the overall field of AI in the public sector.

The thesis also highlights important issues pertaining to the general discipline of AI for the public sector. AI affordance perception and actualisation are two core concepts explored in this thesis. Chapters 3 and 4 of the thesis focus on AI affordance perception, that is, national AI plans of countries and how well they are in accordance with contextual conditions. These plans lend details about social and governance-related issues of AI; however, they do not offer extensive details on how to build the AI enabling capabilities.

However, Chapter 5 focuses on AI affordance actualisation, that is, how public agencies deploy AI systems. Surprisingly, the findings discussed in Chapter 6 indicate that AI enablement components were more knowledgeable and practical areas for public IT managers than social guidance components. The difference between AI affordance perception and actualisation hints at the need for further exploration in the overall area of research. This raises the question for the scholarly community to investigate the reasons for the difference in AI affordance perceptions (national level policy documents) and AI actualisation (public agency level AI deployment). Answers to this question might speed up AI deployment in the public sector under social guidance. A probable reason for this difference could be the communication gap between policy makers and public managers. This contradictory situation between national- and agency-level certainly poses the need for future research.

6.3 Research Contributions

Despite its exploratory nature, this research makes various theoretical and practical contributions to affordances of AI in the public sector context.

6.3.1 Theoretical Contributions

The overall thesis offers multiple theoretical contributions. First, affordance theory was used in this thesis to view technology management in the public sector, which extends understanding of technology affordances for the public sector. Although prior studies have highlighted the affordances of technology artefacts (e.g., Gupta & Bose, 2019; Nambisan et al., 2017; Yoo et al., 2010), there has been limited understanding of how technology artefacts function in the public sector. Previous studies have investigated the affordances of blockchain (e.g., Ostern & Rosemann, 2020) and used the affordance theory to explore digital technologies in general (Mora et al., 2021). AI as a technology artefact is a novel concept in a public sector setting.

Second, the thesis also contributes to the socio-materiality of AI in the public sector by identifying various contextual conditions (technological, economic, social and political factors) that can impact on the actualisation of AI. Much work on the socio-materiality of affordance actualisation has been done previouslyfor private sector organisations (Kummitha, 2020; Leonardi & Barley, 2010; Orlikowski & Scott, 2008). However, exploration of the socio-materiality of technology in a social context has been identified as an opportunity for future research (Kummitha, 2020). The use of signalling theory also identifies which of the contextual conditions impact on the socio-materiality of AI in the public sector setting.

Third, the thesis contributes to AI affordance actualisation through the design and evaluation of the business model of public agencies. Affordance actualisation has been extensively studied as a process for IT-associated organisational change (Strong et al., 2014); however, this thesis presents a novel tool for AI affordance actualisation through the development of the business model.

The contribution overall also extends knowledge on technology management in the public sector and business models of public agencies through individual publications. The methodological contribution of the thesis was primarily focused on using the business model as kernel theory in designing artefacts for public agencies while taking the social, public value, and AI enablement factors into account.

The theoretical contributions of the thesis are based on three studies that contribute to overall goal of the exploration of AI affordances for the public sector.

Study 1 contributes to AI policy analysis and strategic planning in the public sector. It highlights the perception of countries about AI affordances.

The Study 2 offers insights into the implicit message emerging from national AI plans about the perception and actualisation of AI affordances in countries and contributes to the perception and actualisation components of the affordance lens. Study 3 contributes to the existing body of knowledge on AI affordance actualisation by developing an artefact and thus extending knowledge on the actualisation component of affordance theory.

6.3.4 Practical Contributions

The thesis has various practical contributions. First, through analysis of national strategic AI plans of countries, it offers insights into countries that may draft national AI plans. The core elements identified in national AI plans were the use of AI in the public sector and industries. The analysis of the plans also indicated the importance of data and algorithms for AI deployment. This information can help as signposts for countries that intend to formalise AI initiatives at the national level. Finally, AI governance-related topics can also be considered helpful for all countries.

Second, the thesis presents a signal intention and veracity matrix. This matrix compares AI-related goals and contextual conditions of the countries. Policymakers can use the signal intention and veracity matrix as a yardstick to align AI goals and contextual conditions and address any discrepancies. Third, the thesis designed and evaluated a tool for AI-enabled public value called the public AI canvas (PAIC). The PAIC can be used as a tool by public agencies that seek to deploy AI, as well as a helpful guide for public agencies that have already deployed AI. It lists the components related to enablement capabilities, public value logic, and social guidance. It not only sheds information on building capacity for AI but also highlights social costs associated with AI use. Overall, policymakers, industry partners and citizens can use the synopsis of information on AI for the public sector that this thesis presents to make investment or other AI readiness-related decisions about countries.

6.4 Limitations and Future Research

The affordances of AI for the public sector is a contemporary topic with vast research opportunities. This thesis scratched the surface and identified a few components in this regard. The future research areas identified during the thesis include but are not limited to capability development for AI (e.g. existing workforce upskilling for AI expertise, future workforce development), the impact of AI adoption (e.g. citizen interaction, unemployment originated from automation) and regulatory implications for AI (e.g. bias detection and treatment, adherence to citizen privacy etc.). . The trajectory toward AI adoption can change citizens' lives and transform societies. However, how these affordances can be actualised for betterment has not been clear to date. The roadmap to deploy AI for the public sector has been undefined. Therefore, it is vitally important to explore how AI affordances are actualised for the societal good. These insights would make a forward path for AI that will likely impact today's and future lives. Future research projects could include the evaluation of existing AI capabilities and AI aspirations presented in national AI plans.

6.5 Conclusion

This thesis investigates the perception and actualisation of artificial intelligence in the public sector through the lens of technology affordance theory. By reviewing the literature on the digital evolution of the public sector, the thesis acknowledges the existence of AI affordances for the public sector. To understand the perception of AI affordance, the thesis analyses countries' national strategic AI plans and finds that there is variety among perceptions. To investigate the underlying reasons for such differences in perception and consequent actualisation, it employs signalling theory to find the difference between signals conveyed through AI plans and various countries' technical, social, political, and economic conditions. After investigating the use of AI in public agencies, the thesis then designs an artefact grounded on the business model canvas design. The artefact is designed using design science research methodology and the artefact is validated through semi-structured interviews.

The thesis combines three related publications to answer the over-arching research question of AI affordance perception and actualisation in the public sector. It narrows the broad research questions into three sub-questions and answers them through three individual studies. The thesis offers various theoretical contributions, particularly with affordance actualisation by designing and evaluating artefacts. By identifying future research areas, the thesis acknowledges the broad potential of the issue addressed in the thesis, emphasises the topical nature and regards it as a discipline to be researched further. The scope of the thesis is, however, limited due to several reasons.

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Appendices

Appendix A

Countries' Data Set

No.	Country	Strategic plan	Author/issuing agency	Original date issued	Number of pages
1	Australia	AI Roadmap	Department of Industry, Innovation, and Science, Australia and CSIRO's Data 61	November 2019	68
2	Austria	AI Mission Austria 2030	Ministry of Innovation and Technology, Austria	October 2018	16
3	Belgium	AI 4 Belgium	Ministers for Digital Agenda, Belgium	March 2019	29
4	Canada	Pan-Canadian Artificial Intelligence Strategy	Canadian Institute for Advanced Research	March 2017	5
5	China	Next Generation Artificial Intelligence Development Plan	The Foundation for Law and International Affairs, Republic of China	September 2017	28
6	Czech Republic	National Artificial Intelligence Strategy of the Czech Republic	Ministry of Industry and Trade of the Czech Republic	May 2019	54
7	Denmark	National Strategy for Artificial Intelligence	Ministry of Finance and Ministry of Industry, Business and Financial Affairs, Denmark	March 2019	74
8	Estonia	Estonia's National Artificial Intelligence Strategy 2019-2021	Ministry of Economic Affairs and Communications, Estonia	May 2019	47
9	Finland	Finland's Age of Artificial Intelligence	Ministry of Economic Affairs and Employment, Finland	December 2017	76
10	France	For a Meaningful Artificial Intelligence: Towards a French and European Strategy	French Parliament [4]	March 2018	154
11	Germany	AI Strategy	Federal Ministry of Education and Research, the Federal Ministry for Economic Affairs and Energy, and the Federal Ministry of Labour and Social Affairs, Germany	November 2018	45
12	India	National Strategy for AI #AI for All	NITI Aayog[5]	June 2018	115
13	Italy	National Strategy on AI	Italian Ministry of the Economic Development	August 2018	43
14	Japan	AI Technology Strategy	Strategic Council for AI Technology, Japan	March 2017	25

[4] Cedric Villani and Team, task assigned by French Prime Minister Edouard Philippe
[5] Policy Think Tank of Government of India

Appendix A - *continued*

Countries' Data Set

No.	Country	Strategic plan	Author/issuing agency	Original date issued	Number of pages
15	Korea	Mid- to Long-Term Master Plan Intelligent Information Society	Government of the Republic of Korea	December 2016	70
16	Lithuania	Lithuanian Artificial Intelligence Strategy	Ministry of Economy of the Republic of Lithuania	April 2019	22
17	Luxembourg	Artificial Intelligence: A Strategic Vision for Luxembourg	Ministry of Digitalisation, Luxembourg	May 2019	28
18	Malta	The Ultimate AI Launchpad	Parliamentary Secretariat for Financial Services, Digital Economy and Innovation, Malta	October 2019	57
19	Mexico	Toward an AI Strategy in Mexico: Harnessing the AI Revolution	National Digital Strategy Office, Mexico	June 2018	52
20	Netherlands	Strategic Action Plan for AI	Ministry of Economic Affairs, Netherlands	October 2019	64
21	New Zealand	AI Shaping a Future New Zealand	AI Forum New Zealand (AIFNZ)[6]	May 2018	108
22	Norway	National Strategy for Artificial Intelligence	Norwegian Ministry of Local Government and Modernisation	January 2020	67
23	Poland	Poland's Path to the AI Strategy	Polityka Insight[7]	August 2018	40
24	Portugal	AI Portugal 2030	INCoDe.2030[8]	June 2019	36
25	Qatar	National Artificial Intelligence Strategy for Qatar	Qatar Center for Artificial Intelligence	February 2019	16
26	Russia	Development of Artificial Intelligence in the Russian Federation	Office of the President of the Russian Federation	October 2019	18
27	Serbia	Strategy for the Development of Artificial Intelligence in the Republic of Serbia for the Period 2020-2025	Government of Republic of Serbia	November 2019	54
28	Singapore	National AI Strategy	Smart Nation Singapore	November 2019	45
29	Spain	Spanish Strategy for RDI in Artificial Intelligence	Ministry of Science, Innovation and Universities, Spain	March 2019	48
30	Sweden	National Approach to AI	Ministry of Enterprise and Innovation, Sweden	May 2018	12
31	UAE	UAE AI Strategy 2031	National Program for Artificial Intelligence, UAE	October 2017	16

[6] New Zealand's Artificial Intelligence Community
[7] Polish Platform designed for business, CEOs, politicians and ambassadors authorized by Polish Government
[8] Portugal's National Initiative on Digital Competences

Appendix A - *continued*

Countries' Data Set

No.	Country	Strategic plan	Author/issuing agency	Original date issued	Number of pages
32	UK	AI in the UK: ready, willing and able?	Authority of the House of Lords, UK	April 2018	183
33	Uruguay	AI Strategy for the Digital Government	Agency of Electronic Government and Information and Knowledge Society, Uruguay	February 2019	16
34	USA	The National AI Research and Development Strategic Plan	National Science and Technology Council, USA	October 2016	48

Appendix B

Public Functions

Country	Healthcare	Transportation	Education	Environment and natural resources	Energy and utilities	Information and communication Technologies	Public safety	Defence and national security	Courts and the judiciary	Revenue and tax	Immigration, customs and Border protection
Australia	X	X		X	X		X				
Austria							X				
Belgium	X						X		X		
Canada			X								
China	X	X	X	X	X	X	X	X	X		
Czech Republic	X	X				X		X	X		
Denmark	X	X			X					X	
Estonia	X	X					X				
Finland	X	X		X	X		X	X			X
France	X	X		X		X					
Germany	X	X				X	X	X			
India	X	X	X				X				
Italy	X		X	X		X		X	X	X	
Japan	X	X	X	X	X	X					
Korea	X	X	X			X		X			
Lithuania		X			X						
Luxembourg	X	X	X			X					
Malta	X	X	X		X						
Mexico	X	X								X	
Netherlands	X			X							
New Zealand	X	X	X	X							
Norway	X	X		X		X				X	
Poland		X									
Portugal	X	X		X	X	X	X				
Qatar	X	X		X	X			X			
Russia	X		X		X						
Serbia	X	X			X	X					
Singapore	X	X	X			X	X				X
Spain	X	X	X	X	X			X			
Sweden											
UAE		X	X	X	X						
UK	X		X								
Uruguay	X		X								
USA	X	X		X		X	X	X	X		
TOTAL	28	25	15	14	13	13	11	9	5	4	2

Appendix C

Industries

Country	Healthcare	Agriculture	Information technology	Manufacturing	Energy and natural resources	Financial	Defence	Tourism
Australia	X	X				X		
Austria			X	X		X		
Belgium	X		X					
Canada								
China	X	X	X	X	X		X	
Czech Republic	X	X	X	X		X	X	
Denmark	X	X			X			
Estonia		X		X				
Finland				X	X		X	
France					X		X	
Germany	X		X	X				
India	X	X	X		X			
Italy	X	X	X		X			
Japan	X	X	X	X				X
Korea	X	X	X	X		X		
Lithuania		X		X	X			
Luxembourg	X					X		
Malta					X			X
Mexico		X						
Netherlands								
New Zealand	X	X	X	X	X			X
Norway								
Poland	X		X	X	X			X
Portugal	X	X	X		X			
Qatar	X	X			X		X	X
Russia	X		X		X			
Serbia								
Singapore	X			X		X		
Spain		X	X	X	X	X		X
Sweden	X							
UAE	X							
UK			X					
Uruguay								
USA	X	X	X	X		X	X	
TOTAL	20	16	16	14	14	8	6	6

Appendix D

Data

Country	B/W Gov and stakeholders	B/W agencies	B/W Gov and other nations	Data regulations	Privacy	Security
Australia	X	X			X	X
Austria					X	
Belgium	X	X	X	X	X	
Canada						
China	X	X			X	X
Czech Republic	X	X	X	X	X	X
Denmark	X	X	X	X	X	X
Estonia	X	X	X	X	X	
Finland	X	X	X	X		
France	X	X	X	X	X	X
Germany	X	X	X	X	X	X
India	X	X	X	X	X	X
Italy	X	X	X	X	X	X
Japan	X	X		X	X	
Korea	X	X			X	X
Lithuania	X	X	X	X	X	
Luxembourg	X	X	X	X	X	
Malta	X	X	X	X	X	X
Mexico	X	X	X		X	
Netherlands	X	X	X	X	X	
New Zealand	X	X		X	X	
Norway	X	X	X	X	X	
Poland	X			X	X	
Portugal	X	X	X	X	X	
Qatar	X	X	X	X	X	
Russia	X	X		X	X	
Serbia	X	X	X	X	X	
Singapore	X	X		X	X	X
Spain	X	X	X	X	X	X
Sweden	X				X	
UAE						
UK	X	X	X	X	X	
Uruguay	X				X	X
USA	X	X		X	X	
TOTAL	31	28	20	25	31	13

Appendix E

Algorithms

Country	Explainability	Ethics	Bias	Trust
Australia	X	X	X	X
Austria				
Belgium	X	X	X	X
Canada				
China				
Czech Republic				
Denmark	X	X	X	X
Estonia	X		X	
Finland				
France	X	X	X	X
Germany	X	X	X	X
India	X	X	X	X
Italy	X	X	X	X
Japan	X			
Korea			X	
Lithuania	X	X		X
Luxembourg	X			X
Malta	X	X		X
Mexico		X	X	
Netherlands				
New Zealand	X	X	X	X
Norway	X	X	X	X
Poland				
Portugal	X			X
Qatar	X		X	X
Russia	X	X		
Serbia	X	X	X	X
Singapore	X			X
Spain	X	X	X	
Sweden				
UAE				
UK	X	X	X	X
Uruguay	X	X	X	X
USA	X	X	X	X
TOTAL	23	18	18	19

Appendix F

Capacity Development

Country	Higher education	Primary and secondary school	Vocational training	Lifelong learning	Multisectoral research	Research funding	Research institutes	Pilot projects	Attracting ai experts	Procurement	Business model innovation	SMES and startups	Tax incentives
Australia	X	X	X	X	X	X		X					
Austria	X	X				X							
Belgium	X	X	X	X	X	X	X		X	X	X	X	
Canada	X				X	X	X		X				
China	X	X	X	X	X	X	X						X
Czech Republic	X	X	X	X	X	X	X	X	X	X		X	
Denmark	X	X	X	X	X	X	X	X			X	X	X
Estonia	X	X	X		X	X	X	X		X	X	X	
Finland	X		X	X	X	X	X	X	X		X	X	X
France	X	X	X	X	X	X	X	X	X	X	X	X	X
Germany	X	X	X	X	X	X	X	X	X		X	X	X
India	X	X	X		X	X	X	X				X	X
Italy	X	X	X	X	X			X		X	X		X
Japan	X	X	X		X	X	X			X		X	
Korea	X	X			X	X	X			X		X	X
Lithuania	X	X	X		X	X					X		
Luxembourg	X	X	X	X	X	X	X	X			X	X	
Malta	X	X	X	X	X	X	X	X		X		X	X
Mexico	X	X	X	X	X	X	X	X	X	X		X	X
Netherlands			X		X	X						X	
New Zealand	X	X		X	X	X		X	X			X	X

Appendix F - *continued*

Capacity Development

Country	Higher education	Primary and secondary school	Vocational training	lifelong learning	Multisectoral research	Research funding	Research institutes	Pilot projects	Attracting ai experts	Procurement	Business model innovation	SMES and startups	Tax incentives
Norway	**X**	**X**	**X**	**X**	**X**	**X**	**X**	**X**		**X**	**X**	**X**	**X**
Poland			**X**		**X**			**X**					
Portugal	**X**	**X**		**X**	**X**	**X**		**X**	**X**				
Qatar	**X**	**X**		**X**	**X**	**X**	**X**		**X**			**X**	**X**
Russia	**X**	**X**			**X**	**X**	**X**	**X**	**X**				**X**
Serbia	**X**	**X**	**X**	**X**	**X**	**X**	**X**		**X**	**X**	**X**	**X**	**X**
Singapore	**X**	**X**			**X**		**X**						
Spain	**X**		**X**	**X**	**X**	**X**	**X**	**X**	**X**	**X**		**X**	
Sweden	**X**			**X**				**X**					
UAE			**X**	**X**			**X**						
UK	**X**	**X**	**X**	**X**	**X**	**X**	**X**	**X**	**X**	**X**		**X**	**X**
Uruguay	**X**				**X**			**X**					
USA	**X**	**X**	**X**	**X**	**X**	**X**	**X**					**X**	
TOTAL	31	26	24	22	31	28	24	21	14	13	11	21	16

Appendix G
AI Governance

Country	Regulations	Risks	Social and economic inequality	Security	Intellectual property rights protection	Interoperability
Australia	X	X		X		X
Austria	X		X			
Belgium	X	X	X		X	X
Canada	X		X			
China	X	X	X	X	X	
Czech Republic	X	X	X	X	X	
Denmark	X	X	X	X		
Estonia	X	X		X	X	X
Finland	X	X	X	X		
France	X	X	X	X	X	X
Germany	X	X	X	X	X	X
India	X	X	X		X	
Italy	X	X	X	X	X	X
Japan	X					
Korea	X	X	X	X		
Lithuania	X	X	X	X		
Luxembourg	X	X		X		
Malta	X	X	X	X	X	X
Mexico	X	X	X		X	X
Netherlands	X					
New Zealand	X	X	X	X	X	
Norway	X	X	X	X	X	X
Poland	X			X		
Portugal	X	X	X	X		
Qatar	X		X			
Russia	X	X			X	
Serbia	X	X	X	X	X	X
Singapore	X	X				
Spain	X	X	X			
Sweden	X	X				
UAE	X			X		
UK	X	X	X	X	X	X
Uruguay	X	X	X			
USA	X	X	X	X		
TOTAL	34	27	24	21	15	11

Appendix H

Uncalibrated Dataset Conditions

Country	Democracy (Ratio Scale 1-10) 2019	Judicial Independence 2019 (Scale 1-7)	Political Stability 2019 (Scale -2.5-2.5)	Electoral Democracies 2016 (1=yes, 0= No)	Ability to reform: social 2016 (Scale 0-4)	Ability to reform: health and education 2016 (Scale 0-4)	Ability to reform: societal 2016 (Scale 0-4)	Future Orientation of Government 2018 (Scale 1-7)	Public authorities support to Innovation (public or private R&D) 2016 (Scale 0-4)	Technological environment of firms 2016 (Scale 0-4)	Public trust in politicians 2017 (Score 1-7)	Diversion of public funds 2017 (Scale 1-7)	Freedom of access on the Internet 2016 (Scale 0-4)	Freedom of elections 2016 (Scale 0-4, 99= No election)	Voice and accountability 2019 (Scale -2.5 - 2.5)	Population participation (national level) 2016 (Scale 0-4)	Population participation (local level) 2016 (Scale 0-4)
Australia	9.09	5.98	1.09	1	4	4	4	4.18	3	2.67	4.64	5.68	4	4	1.32	4	4
Austria	8.29	5.66	0.98	1	2	2	2	4.24	4	3.00	4.15	4.75	4	4	1.33	4	4
Belgium	7.64	5.74	0.48	1	4	4	4	3.83	3	3.00	4.20	4.94	4	4	1.37	2	3
Canada	9.22	5.65	1.03	1	4	4	4	4.41	4	3.67	4.98	5.45	4	4	1.46	2	3
China	2.26	7.00	-0.24	0	3	3	4	4.38	4	3.00	4.47	4.14	2	99	-1.61	4	4
Czech Republic	7.69	4.49	0.95	1	3	2	3	3.21	3	1.67	2.58	2.90	4	4	0.94	0	0
Denmark	9.22	6.17	1.01	1	4	4	4	4.73	3	2.67	5.11	5.73	4	4	1.58	3	3
Estonia	7.9	5.41	0.64	1	3	3	3	4.08	3	2.33	3.77	4.64	4	4	1.21	3	3
Finland	9.25	6.64	0.91	1	3	3	3	5.13	3	4.00	5.80	6.35	4	4	1.59	0	1
France	8.12	4.88	0.31	1	3	3	4	4.06	4	3.33	3.65	4.97	4	4	1.14	2	2
Germany	8.68	5.01	0.58	1	4	4	3	5.05	4	4.00	5.14	5.23	4	4	1.34	2	2
India	6.9	4.29	-0.70	1	1	1	0	4.65	1	1.67	4.19	4.55	3	4	0.29	4	4
Italy	7.52	4.02	0.46	1	3	3	2	2.66	2	3.00	1.86	3.29	4	4	0.97	4	4
Japan	7.99	6.19	1.04	1	2	2	2	4.65	4	4.00	4.51	5.33	4	4	0.96	3	3
Korea.	8	3.93	0.48	1	3	4	3	4.01	4	3.00	2.53	3.75	4	4	0.77	3	3
Lithuania	7.5	4.21	0.84	1	4	3	4	3.46	1	2.33	2.81	3.57	4	4	1.02	2	3
Luxembourg	8.81	6.09	1.36	1	4	4	4	5.74	3	3.00	5.61	5.97	4	4	1.52	3	3
Malta	7.95	3.97	1.09	1	3	4	3	4.61	3	3.00	2.91	4.15	4	4	1.11	3	4
Mexico	6.09	2.99	-0.71	1	3	3	2	3.38	3	1.67	1.69	2.20	2	4	0.02	3	3

Netherlands	9.01	6.24	0.86	1	3	4	2	4.99	3	3.33	5.63	6.00	4	4	1.56	4	4
New Zealand	9.26	6.35	1.51	1	4	4	4	4.95	1	1.67	6.06	6.45	4	4	1.57	1	2
Norway	9.87	6.01	1.19	1	4	4	4	4.78	3	3.33	5.71	5.94	4	4	1.69	3	3
Poland	6.62	2.66	0.52	1	3	3	3	3.12	4	1.67	2.26	3.76	4	4	0.70	4	4
Portugal	8.03	4.53	1.13	1	4	4	3	3.71	3	2.67	3.21	4.11	4	4	1.24	4	4
Qatar	3.19	5.40	0.70	0	3	3	3	5.26	3	2.33	5.92	6.06	3	99	-1.29	3	2
Russia	3.11	3.23	-0.54	0	3	3	3	3.87	3	3.00	3.43	3.23	3	3	-1.10	3	3
Serbia	6.41	3.05	-0.09	1	2	2	2	3.55	2	2.67	2.63	3.15	4	2	0.03	0	0
Singapore	6.02	5.65	1.53	0	4	3	3	6.14	4	3.33	6.42	6.16	2	3	-0.18	4	4
Spain	8.29	4.17	0.32	1	3	2	3	3.41	2	1.67	2.24	2.95	4	4	1.09	2	2
Sweden	9.39	5.61	1.05	1	4	4	4	4.84	3	3.33	5.24	5.71	4	4	1.59	2	2
United Arab	2.76	5.52	0.70	0	4	4	2	5.60	2	2.33	6.31	6.17	2	99	-1.12	3	3
United Kingdom	8.52	5.17	0.52	1	4	3	3	4.55	3	3.33	4.81	5.83	4	4	1.26	4	4
United States	7.96	5.22	0.30	1	2	1	2	5.70	3	4.00	4.85	5.17	4	4	0.97	2	2
Uruguay	8.38	5.32	1.05	1	3	3	3	3.65	2	2.67	4.35	4.26	4	4	1.26	3	3

Appendix I

Uncalibrated Outcomes Data

Country	Public services *n*	Research	Data	Algorithms	Governance
Australia	5	2	6	4	4
Austria	1	1	1	0	2
Belgium	3	3	9	4	5
Canada	1	3	0	0	2
China	9	3	6	0	5
Czech Republic	4	3	10	0	5
Denmark	4	3	10	4	4
Estonia	3	3	9	2	5
Finland	7	3	8	0	4
France	4	3	10	4	6
Germany	5	3	8	4	6
India	4	3	10	4	4
Italy	7	1	10	4	6
Japan	6	3	7	1	1
Korea	5	3	5	1	4
Lithuania	2	2	10	3	4
Luxembourg	4	3	9	2	3
Malta	4	3	10	3	6
Mexico	3	3	7	2	5
Netherlands	2	2	9	0	1
New Zealand	4	2	7	4	5
Norway	4	3	9	4	6
Poland	1	1	5	0	2
Portugal	6	2	9	2	4
Qatar	5	3	9	3	2
Russia	3	3	7	2	3
Serbia	4	3	10	4	6
Singapore	6	2	8	2	2
Spain	6	3	10	3	3
Sweden	1	0	3	0	2
United Arab Emirates	4	1	0	0	2
United Kingdom	2	3	9	4	6
United States of America	7	3	6	4	4
Uruguay	3	1	5	4	3

Appendix J

Calibrated Conditions Data

Country	Democracy	Effective government	Reform orientation	Political participation	Technical environment
Australia	0.984237362	0.818821962	0.971358	0.947864	0.630290412
Austria	0.954143478	0.768832094	0.275864	0.94752	0.927875325
Belgium	1	0.741890598	0.926546	0.5738	0.651927572
Canada	1	0.832747874	0.963088	0.591386	0.971067801
China	0	0.766661437	0.642654	0.994862	0.931512391
Czech Republic	0.975060314	0.354349207	0.369613	0	0.304113949
Denmark	1	0.894615161	0.981439	0.704608	0.643640004
Estonia	0.969321753	0.673963915	0.577261	0.692266	0.538870757
Finland	1	0.941684197	0.625803	0.08167	0.856655776
France	0.987426197	0.69453418	0.670632	0.440978	0.923390647
Germany	0.978436494	0.842555099	0.807755	0.486541	1
India	0.692898532	0.632085071	0	0.940974	0.005903812
Italy	0.93478241	0.185654508	0.309768	0.917344	0.399572329
Japan	0.929927644	0.804083506	0.265512	0.702156	1
Korea	0.931596159	0.533572845	0.586777	0.720951	0.833940608
Lithuania	0.962624435	0.515234839	0.665571	0.49847	0.090389793
Luxembourg	0.983977641	0.980282919	0.985613	0.70278	0.736271069
Malta	0.953309506	0.62348688	0.595853	0.823946	0.695270649
Mexico	0.611161606	0.088503319	0.249252	0.758101	0.309144135
Netherlands	0.966885771	0.931410518	0.648345	0.98458	0.773383962
New Zealand	1	0.909192463	0.981972	0.306985	0
Norway	0.999093925	0.918531879	0.981295	0.698471	0.75135398
Poland	0.837730621	0.186057734	0.478288	0.953947	0.542229809
Portugal	0.97259102	0.602061834	0.745092	0.953439	0.574322614
Qatar	0	0.93008557	0.59315	0.62414	0.598954121
Russia	0.136127809	0.516724111	0.399011	0.744843	0.678875503
Serbia	0.657353842	0.262810415	0.028246	0	0.290520428
Singapore	0.241764869	1	0.746709	1	1
Spain	0.980284552	0.394746661	0.341442	0.39336	0.171789966
Sweden	1	0.857867479	0.949667	0.452825	0.717727405
United Arab Emirates	0	0.97554486	0.68169	0.805701	0.360020443
United Kingdom	0.956949746	0.80519155	0.716511	0.941081	0.719505088
United States of America	0.914816519	0.815973017	0.104203	0.409452	0.891661673
Uruguay	0.980802529	0.689722262	0.542528	0.661825	0.415032213

Appendix K

Calibrated Outcomes Data

Country	Public services	Research	Data	Algorithmic ethics	Governance
Australia	0.5001	0.666667	0.666667	1	0.75
Austria	0	0.333333	0	0	0.25
Belgium	0.166667	1	1	1	1
Canada	0	1	0	0	0.25
China	1	1	0.666667	0	1
Czech Republic	0.333333	1	1	0	1
Denmark	0.333333	1	1	1	0.75
Estonia	0.166667	1	1	0.5001	1
Finland	0.833333	1	1	0	0.75
France	0.333333	1	1	1	1
Germany	0.5001	1	1	1	1
India	0.333333	1	1	1	0.75
Italy	0.833333	0.333333	1	1	1
Japan	0.666667	1	0.833333	0.25	0
Korea	0.5001	1	0.5001	0.25	0.75
Lithuania	0	0.666667	1	0.75	0.75
Luxembourg	0.333333	1	1	0.5001	0.5001
Malta	0.333333	1	1	0.75	1
Mexico	0.166667	1	0.833333	0.5001	1
Netherlands	0	0.666667	1	0	0
New Zealand	0.333333	0.666667	0.833333	1	1
Norway	0.333333	1	1	1	1
Poland	0	0.333333	0.5001	0	0.25
Portugal	0.666667	0.666667	1	0.5001	0.75
Qatar	0.5001	1	1	0.75	0.25
Russia	0.166667	1	0.833333	0.5001	0.5001
Serbia	0.333333	1	1	1	1
Singapore	0.666667	0.666667	1	0.5001	0.25
Spain	0.666667	1	1	0.75	0.5001
Sweden	0	0	0.166667	0	0.25
United Arab Emirates	0.333333	0.333333	0	0	0.25
United Kingdom	0	1	1	1	1
United States of America	0.833333	1	0.666667	1	0.75
Uruguay	0.166667	0.333333	0.5001	1	0.5001

Appendix L

Table L1

Truth Table - Public Services

Democracy	EffGov	Reform	PolPart	TechEnv	number	PublicServices	raw consist.	PRI consist.	SYM consist
1	1	0	0	1	1	0	0.852253	0.487767	0.487767
0	1	1	1	1	3	0	0.793545	0.564278	0.627014
0	1	0	1	1	1	0	0.757181	0.347252	0.347252
1	1	1	0	1	4	0	0.693255	0.184506	0.185502
1	0	0	1	1	1	0	0.660251	0.129482	0.129482
0	1	1	1	0	1	0	0.65188	0.080455	0.080455
1	1	1	0	0	2	0	0.64745	0.00434	0.004402
1	0	0	0	0	3	0	0.64543	0.147825	0.147825
1	1	0	1	1	2	0	0.631407	0.20319	0.205682
1	1	1	1	0	1	0	0.616199	0.04649	0.04649
1	0	0	1	0	2	0	0.609458	0.198881	0.198881
1	1	0	1	0	1	0	0.565441	0.037561	0.037561
1	1	1	1	1	12	0	0.497071	0.044676	0.046524

Table L2

Truth Table - Public Services (N)

Democracy	EffGov	Reform	PolPart	TechEnv	number	~PublicServices	raw consist.	PRI consist.	SYM consist
1	1	1	0	0	2	1	0.99347	0.981558	0.995598
1	1	0	1	0	1	1	0.98304	0.962439	0.962439
1	1	1	1	0	1	1	0.981287	0.95351	0.95351
0	1	1	1	0	1	1	0.969542	0.919545	0.919545
1	1	1	1	1	12	1	0.955562	0.91559	0.953476
1	0	0	1	1	1	1	0.949465	0.870517	0.870518
1	0	0	0	0	3	1	0.938493	0.852175	0.852175
1	1	1	0	1	4	1	0.92858	0.810128	0.814498
1	0	0	1	0	2	1	0.903046	0.801119	0.801119
1	1	0	1	1	2	1	0.900402	0.784693	0.794318
0	1	0	1	1	1	1	0.870824	0.652748	0.652748
1	1	0	0	1	1	0	0.859309	0.512233	0.512233
0	1	1	1	1	3	0	0.685224	0.335667	0.372986

Appendix L - *continued*

Table L3

Truth Table - Research

Democracy	EffGov	Reform	PolPart	TechEnv	number	Research	raw consist.	PRI consist.	SYM consist
0	1	0	1	1	1	1	1	1	1
1	0	0	0	0	3	1	0.988615	0.985568	0.985568
1	1	0	0	1	1	1	0.987706	0.985451	0.985451
0	1	1	1	1	3	1	0.970768	0.958604	0.989317
1	1	0	1	0	1	1	0.962552	0.942234	0.942234
1	1	1	1	1	12	1	0.951717	0.938965	0.938965
1	1	1	0	0	2	1	0.940594	0.921267	0.927405
1	0	0	1	1	1	1	0.938423	0.907638	0.907638
1	1	1	1	0	1	1	0.923001	0.879306	0.879306
1	1	0	1	1	2	1	0.917422	0.879642	0.891435
1	1	1	0	1	4	1	0.916595	0.90643	0.90643
1	0	0	1	0	2	1	0.913241	0.867723	0.867723
0	1	1	1	0	1	1	0.863626	0.796792	0.796792

Table L4

Truth Table - Research (N)

Democracy	EffGov	Reform	PolPart	TechEnv	number	~Research	raw consist.	PRI consist.	SYM consist
0	1	1	1	0	1	0	0.465267	0.203208	0.203208
1	1	1	1	0	1	0	0.43903	0.120694	0.120694
1	0	0	1	0	2	0	0.43087	0.132277	0.132277
1	0	0	1	1	1	0	0.394883	0.092362	0.092362
1	1	0	1	0	1	0	0.389174	0.057766	0.057766
1	1	0	1	1	2	0	0.387399	0.107129	0.108565
0	1	0	1	1	1	0	0.353463	0	0
0	1	1	1	1	3	0	0.301157	0.010351	0.010683
1	1	1	0	0	2	0	0.29989	0.072115	0.072595
1	1	1	1	1	12	0	0.257217	0.061035	0.061035
1	0	0	0	0	3	0	0.222525	0.014432	0.014432
1	1	1	0	1	4	0	0.192043	0.09357	0.09357
1	1	0	0	1	1	0	0.167273	0.014549	0.014549

Appendix L - *continued*

Table L 5

Truth Table - Data

Democracy	EffGov	Reform	PolPart	TechEnv	number	Data	raw consist.	PRI consist.	SYM consist
1	0	0	0	0	3	1	0.981585	0.975988	0.975988
1	0	0	1	0	2	1	0.980158	0.972319	0.972319
1	1	0	0	1	1	1	0.980082	0.97041	0.97041
1	1	0	1	0	1	1	0.978309	0.970447	0.970447
1	1	1	0	0	2	1	0.962662	0.950894	0.950894
1	1	1	1	0	1	1	0.959408	0.942872	0.951776
1	0	0	1	1	1	1	0.941504	0.903322	0.909885
1	1	1	1	1	12	1	0.892791	0.867746	0.870995
0	1	1	1	1	3	1	0.888835	0.846359	0.846359
1	1	0	1	1	2	1	0.879798	0.831384	0.831384
1	1	1	0	1	4	1	0.872842	0.839418	0.839418
0	1	0	1	1	1	1	0.868359	0.792729	0.792729
0	1	1	1	0	1	0	0.694989	0.564297	0.564297

Table L6

Truth Table - Data (N)

Democracy	EffGov	Reform	PolPart	TechEnv	number	~Data	raw consist.	PRI consist.	SYM consist
0	1	1	1	0	1	0	0.604968	0.435703	0.435703
0	1	0	1	1	1	0	0.496523	0.207271	0.207271
1	0	0	1	1	1	0	0.449071	0.089466	0.090116
1	1	0	1	1	2	0	0.407329	0.168616	0.168616
0	1	1	1	1	3	0	0.387627	0.153641	0.153641
1	1	0	0	1	1	0	0.346769	0.02959	0.02959
1	1	1	0	1	4	0	0.335298	0.160582	0.160582
1	1	1	1	0	1	0	0.323397	0.047773	0.048224
1	0	0	1	0	2	0	0.303022	0.027681	0.027681
1	1	1	1	1	12	0	0.293557	0.128524	0.129005
1	1	0	1	0	1	0	0.287747	0.029554	0.029554
1	1	1	0	0	2	0	0.276995	0.049106	0.049106
1	0	0	0	0	3	0	0.251513	0.024012	0.024012

Appendix L - *continued*

Table L7

Truth Table - Algorithms

Democracy	EffGov	Reform	PolPart	TechEnv	number	Algorithms	raw consist.	PRI consist.	SYM consist
1	1	1	1	0	1	1	0.862494	0.785493	0.785493
1	1	0	1	0	1	1	0.861401	0.771526	0.771527
1	0	0	1	0	2	1	0.833669	0.71241	0.740324
1	1	1	0	0	2	1	0.825107	0.743074	0.743074
1	0	0	0	0	3	1	0.800515	0.688606	0.688606
1	1	0	0	1	1	0	0.786895	0.676497	0.676497
1	0	0	1	1	1	0	0.771773	0.617334	0.617334
1	1	1	1	1	12	0	0.742483	0.647709	0.674001
1	1	1	0	1	4	0	0.691137	0.57449	0.574489
1	1	0	1	1	2	0	0.676827	0.508233	0.508233
0	1	0	1	1	1	0	0.662545	0.313552	0.317433
0	1	1	1	1	3	0	0.591762	0.289323	0.327875
0	1	1	1	0	1	0	0.577638	0.292659	0.292659

Table L8

Truth Table - Algorithms (N)

Democracy	EffGov	Reform	PolPart	TechEnv	number	~Algorithms	raw consist.	PRI consist.	SYM consist
0	1	0	1	1	1	1	0.83985	0.674224	0.682567
0	1	1	1	0	1	1	0.82525	0.707341	0.707341
0	1	1	1	1	3	0	0.766259	0.593095	0.672125
1	1	0	1	1	2	0	0.666006	0.491767	0.491767
1	0	0	1	1	1	0	0.631814	0.382666	0.382666
1	1	1	0	1	4	0	0.582999	0.425511	0.425511
1	0	0	1	0	2	0	0.566163	0.249885	0.259676
1	0	0	0	0	3	0	0.558866	0.311394	0.311394
1	1	0	0	1	1	0	0.554364	0.323503	0.323503
1	1	0	1	0	1	0	0.53197	0.228473	0.228473
1	1	1	1	1	12	0	0.498025	0.313282	0.325999
1	1	1	1	0	1	0	0.496474	0.214507	0.214507
1	1	1	0	0	2	0	0.49418	0.256926	0.256926

Appendix L - *continued*

Table L9

Truth Table - Governance

Democracy	EffGov	Reform	PolPart	TechEnv	number	Governance	raw consist.	PRI consist.	SYM consist
1	1	1	0	0	2	1	0.990962	0.983012	0.983012
1	0	0	0	0	3	1	0.972727	0.952661	0.993685
1	1	1	1	0	1	1	0.952792	0.90736	0.919353
1	1	0	1	0	1	1	0.95136	0.895422	0.895422
1	0	0	1	0	2	1	0.945738	0.897931	0.897931
1	1	0	0	1	1	1	0.930199	0.884046	0.884046
1	0	0	1	1	1	1	0.891724	0.812871	0.812871
1	1	1	0	1	4	1	0.888688	0.817345	0.817345
0	1	0	1	1	1	1	0.874108	0.656883	0.667821
1	1	1	1	1	12	1	0.847652	0.771889	0.793644
1	1	0	1	1	2	0	0.758672	0.603526	0.603526
0	1	1	1	0	1	0	0.744664	0.382809	0.382809
0	1	1	1	1	3	0	0.711577	0.474755	0.474755

Table L10

Truth Table - Governance (N)

Democracy	EffGov	Reform	PolPart	TechEnv	number	~Governance	raw consist.	PRI consist.	SYM consist
0	1	1	1	0	1	1	0.841629	0.617191	0.617191
0	1	0	1	1	1	0	0.752977	0.326739	0.33218
0	1	1	1	1	3	0	0.739302	0.525245	0.525245
1	1	0	1	1	2	0	0.632643	0.396474	0.396474
1	1	0	1	0	1	0	0.583531	0.104578	0.104578
1	1	1	1	0	1	0	0.530979	0.079596	0.080648
1	0	0	1	1	1	0	0.529661	0.187129	0.187129
1	0	0	1	0	2	0	0.522639	0.102069	0.102069
1	1	1	0	1	4	0	0.501902	0.182655	0.182655
1	1	1	0	0	2	0	0.476994	0.016988	0.016988
1	1	0	0	1	1	0	0.467827	0.115954	0.115954
1	1	1	1	1	12	0	0.466171	0.200699	0.206356
1	0	0	0	0	3	0	0.427373	0.006054	0.006315

Appendix M

Case Study: AI-Enabled Fire Prediction System, WIFIRE

Public value-oriented social guidance Layer				
Social drivers 1. Safety of citizens	Social objectives 1. Disaster detection method 2. Wildfire protection		Social viability	
Public value logic layer				
Citizens and clients 1. Employees in FEMA 2. Local communities affected by fires	Key stakeholders 1. Federal Emergency Management Agency (FEMA) 2. Los Angeles Fire Department 3. Fennessy and the Orange County Fire Authority 4. University of California 5. Federal, State and Local Governments in California			
Public value-oriented AI-enablement layer				
Data 1. Minute atmospheric pressure readings 2. Social media data 3. Xview2 disaster image dataset 4. Private satellite data 5. Geospatial data	Algorithms 1. To learn building images from satellite data	AI Capabilities 1. WIFIRE 2. FIRIS	Public value proposition 1. Efficiency 2. Effectiveness	Economic viability

Appendix N

Exemplar Questions

Key issue	Exemplar question
Completeness	1. What would you like to say about the scope of the canvas? Is the canvas sufficiently broad in scope to cover all necessary key elements when it comes to AI systems in the public sector? 2. What would you like to say about the scope of the AI-enablement layer? Is the layer sufficiently broad in scope to cover all necessary key elements when it comes to AI enablement in the public sector?
Fidelity with the real world	1. Can you envision yourself using the canvas in your agency? 2. Can you think of a future project that you are considering, or a past project that you have completed, and tell us how the canvas might, or would have, been used?
Internal consistency	1. What are your thoughts about the layers of the canvas? Does each layer have elements that are cohesive? 2. Do you think the components in each layer of the canvas are adequately linked/connected?
Level of detail	1. Do you think there are components missing? 2. Do you think there are components that could be left out?
Robustness	1. Do you think the canvas is expected to work in different contexts such as other technologies (e.g., quantum computing), in the public agencies? 2. What issues might you run into as you use the canvas in your agency?

Appendix O
Codebook

First order concepts	Second order themes	Codes	Description
Scope of canvas layers	Scope of AI-enablement layer		The degree to which interviewees agree/disagree to the idea of AI layer
		Data	The degree to which interviewees agree/disagree to the effectiveness of data component
		Algorithms	The degree to which interviewees agree/disagree to the effectiveness of algorithms component
		AI capabilities	The degree to which interviewees agree/disagree to the effectiveness of AI capabilities component
		Public value proposition	The degree to which interviewees agree/disagree to the idea of Public Value Proposition component
		Economic viability	The degree to which interviewees agree/disagree to the effectiveness of Economic Viability component
Scope of canvas layers	Scope of public value logic layer		The degree to which interviewees agree/disagree to the idea of Public Value Logic Layer
		Citizens and clients	The degree to which interviewees agree/disagree to the effectiveness of Citizens and Clients component
		Key stakeholders	The degree to which interviewees agree/disagree to the idea of Key Stakeholders component

Appendix O - *continued*

Codebook

First order concepts	Second order themes	Codes	Description
Scope of canvas layers	Scope of social guidance layer components		The degree to which interviewees agree/disagree to the effectiveness of Social Drivers component
		Social objectives	The degree to which interviewees agree/disagree to the effectiveness of Social Objectives component
		Social viability	The degree to which interviewees agree/disagree to the effectiveness of Social Viability component
Scope of overall canvas			The degree to which interviewees agree to the effectiveness of overall canvas
	Placement of layers		Opinion of interviewees about the placement (sequence) of layers
	Graphical representation		Opinion of interviewees about the graphical representation of layers
	Perationalization of components		Opinion of interviewees about the operationalization of layers
	Brevity of layers		Opinion of interviewees about the extent of details
	Rephrasing of components		The suggested phrase/label given by interviewee
	Reordering of components		Suggestions by interviewees to reorder/move the components between and among the layers
	Addition of components		The new component(s) suggested by interviewee
	Removal of components		Any removal/merge of components suggested by interviewee