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Public AI canvas for AI-enabled public value: A design science approach

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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. Introduction

With rapid advancements in artificial intelligence (AI), the public sector has shown great interest in AI deployment (Sharma, Yadav, & Chopra, 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, Kok Heang, Clogher, & McBride, 2019; Danaher et al., 2017; Engin & Treleaven, 2019; Wang, Teo, & Janssen, 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, & Chenok, 2020; Mikalef, Fjørtoft, & Torvatn, 2019; Mikhaylov, Esteve, & Campion, 2018). 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, Henriksen, & Hedman, 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 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, Župič, & Trkman, 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, Tuunanen, Rothenberger, & Chatterjee, 2007). According to DSRM, an artifact, object, or instantiation is designed to solve a problem. DSRM is widely applied in information systems research (Hevner, March, Park, & Ram, 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.

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The structure of the paper 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.

2. Background

2.1. 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, Tucci, & Afuah, 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.

2.2. Business model and the 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, Finnegan, & Nilsson, 2011), and sustainability (Pieroni, McAloone, & Pigosso, 2019). Few studies have applied the business model concept to the aspects of the public sector, such as e-government (Janssen, Kuk, & Wagenaar, 2008), urban services in smart cities (Díaz-Díaz, Muñoz, & Pérez-González, 2017), ICT-supported citizen engagement (Panagiotopoulos, Al-Debei, Fitzgerald, & Elliman, 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, Madsen, Hofmann, & Melin, 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).

2.3. 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, Short, Rana, & Evans, 2014; Wallin, Chirumalla, & Thompson, 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, Sprenkels, Peeters, and Janssen (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.

2.4. AI frameworks for public management

Public sector–specific frameworks for AI deployment are limited (Zuiderwijk, Chen, & Salem, 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, Weyerer, and Sturm (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.

3. 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, Lewis, Nicholls, & Ormston, 2013). More often, qualitative research methods have been proposed for validation or evaluation of the artifacts designed in DSRM (Kuechler, Park, & Vaishnavi, 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, Bockstedt, Gupta, & Kauffman, 2008; Hoch & Brad, 2020; Peffers et al., 2007). Using expert interviews to evaluate artifacts has been a common practice in DSRM (Offermann, Levina, Schönherr, & Bub, 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.

3.1. 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, Oliver, Letouzé, Pentland, & Vinck, 2018). 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, Wachter, Mittelstadt, Taddeo, & Floridi, 2018; Margetts & Dorobantu, 2019; 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.

3.2. 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, de Reuver, Heikkilä, & Fielt, 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.

4. Conceptual development of public ai canvas (PAIC)

4.1. 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 (noncommercial) 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 Fig. 1.

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 (Fig. 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

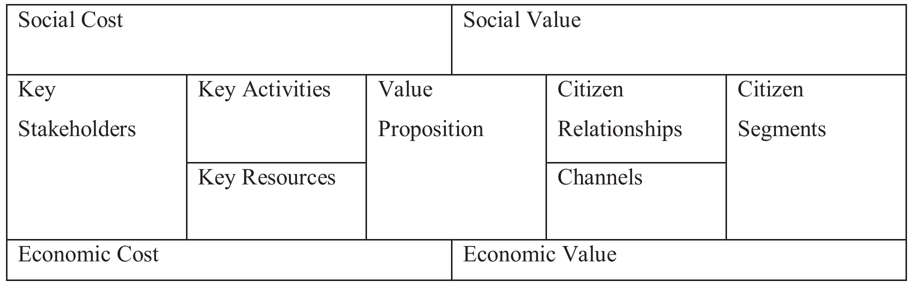

Fig. 1. First iteration of BMC.

social components. It was challenging to understand which components belonged to which building block. The single-layered BMC is shown in Fig. 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 Fig. 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.

4.2. 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, Hinnant, & Moon, 2005) and are not limited to citizens'

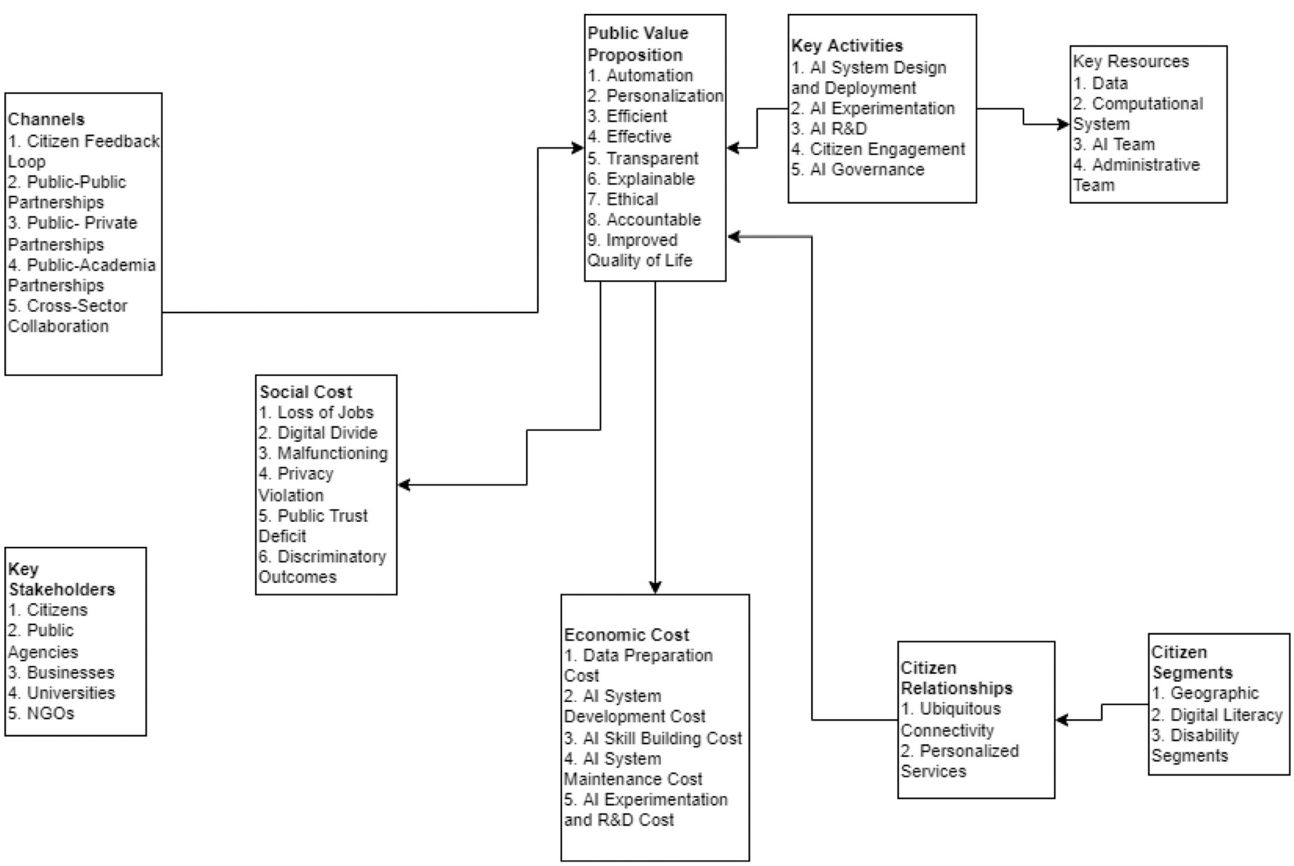

Fig. 2. Third iteration of BMC.

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[1]

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

Fig. 3. Designed artifact: public AI canvas (PAIC).

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 Fig. 3. Next, we will describe each layer in more detail.

4.2.1. 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.

4.2.1.1. 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 (Dey, 2016) and sabotage the objective of public value creation (Janssen & Kuk, 2016). 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.

4.2.1.2. 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, 2016). The explainability of algorithmic output unfolds the logic used and adds to the public value (Zerilli, Knott, Maclaurin, & Gavaghan, 2018). Therefore, PAIC proposes that regularizing algorithms for public value propositions such as transparency, explainability, and accountability is unavoidable for public agencies.

4.2.1.3. 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.

4.2.1.4. 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, Esteve, & Mikhaylov, 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, Rodríguez Bolívar, & López Hernández, 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, Allo, Taddeo, Wachter, & Floridi, 2016) 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.

4.2.1.5. 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.

4.2.2. 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.

4.2.2.1. 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.

4.2.2.2. Key stakeholders. Public agencies deal with various stakeholders (de Vries, Tummers, & Bekkers, 2018). Identifying key stakeholders is essential for actualizing AI-enabled initiatives (Sun & Medaglia, 2019). Based on a literature review (Hwabamungu, Brown, & Williams, 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.

4.2.3. 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.

4.2.3.1. 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., 2018). 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.

4.2.3.2. 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, Noorman, & Martin, 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., 2018). 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, 2016), and real-time data-based traffic predictions can improve public transport (Kankanhalli, Charalabidis, & Mellouli, 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.

4.2.3.3. 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 socio-economic 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.

4.3. 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. Second, the adaptation of the BMC building blocks into PAIC is shown in Fig. 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) (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.

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 Fig. 3. Now, we will explain in detail the three layers of the PAIC.

5. 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.

5.1. 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

<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>

Fig. 4. PAIC positioned in the BMC.

case to demonstrate the artifact (PAIC).

5.1.1. 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 A.

5.2. Evaluation of PAIC

5.2.1. Expert interviews

To evaluate PAIC, we examined guidelines by Peffers, Rothenberger, Tuunanen, and Vaezi (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, Mueller, and Sugumaran (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.

5.2.1.1. 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, Donnellan, and Ostrowski (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 1. The identity of interviewees would be disclosed if the country name were included in the demographics in Table 1.

5.2.1.2. 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 B.

On average, the interviews lasted for an hour, with 10 to 15 min 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 analyzed 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 &

Table 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

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 C, 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.

5.2.2. 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.

5.2.2.1. Overall artifact evaluation. We used Sonnenberg and Vom Brocke (2012) method for the overall artifact evaluation. They identified five criteria for artifacts designed as models (Table 2).

5.2.2.2. Completeness. The interviewees agreed that the artifact was complete, in terms of covering the necessary components. As shown in the exemplar quotation (Table 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.

5.2.2.3. 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."*

5.2.2.4. 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."*

5.2.2.5. 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 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.

5.2.2.6. Robustness. According to Sonnenberg and Vom Brocke (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."*

Table 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 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.	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.
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.
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.

5.2.2.7. Evaluation of PAIC layers. In the next section, we present each layer with exemplar quotations. A detailed codebook is provided in Appendix C.

5.2.2.8. 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.

5.2.2.9. 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?"*

5.2.2.10. 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 non-validating, 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.

5.2.2.11. 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 3. This table presents the following themes: placement, graphical representation of layers and addition, deletion, reordering, rephrasing, and brevity of the components. Table 3 shows the key insights regarding the themes, exemplar quotations, and actions

Table 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 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.*	Added in public value-oriented AI-enablement layer.
	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 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.	1. *We just call universities 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.*	1. Five updates (rephrasing) made in updated PAIC.

taken to update the canvas.

6. Findings: Postvalidation PAIC

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

6.1. 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.

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

6.1.1.1. 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.

Public value logic layer	
Citizens and clients	Key stakeholders
• Public Value • Private Value	• Public Agencies • Employees • Businesses • Academia • Technology Companies • Nonprofits

(*continued on next page*)

(*continued*)

Public value logic layer	
Citizens and clients	Key stakeholders
	• Entrepreneurial Hubs • Politicians • Regulators

6.1.1.2. 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.

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 o Privacy Violation o Disparate Treatment o 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 Fig. 5.

7. 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

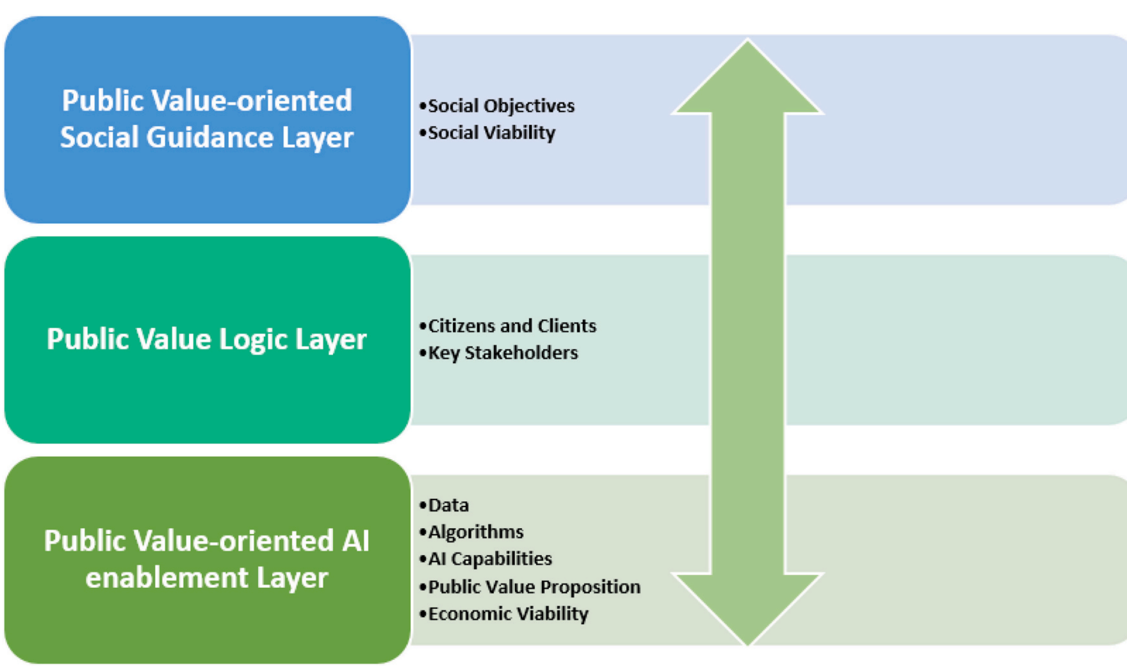

Fig. 5. Updated PAIC.

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.

8. 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.

8.1. 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, vom Brocke, and Maedche (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.

8.2. Practical contributions

Significant initiatives for AI deployment in public agencies are evident (Fatima, Desouza, & Dawson, 2020). 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).

8.3. 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, Elikan, Missionier, & Pigneur, 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.

CRediT authorship contribution statement

Samar Fatima: Conceptualization, Methodology, Software, Writing – original draft. **Kevin C. Desouza:** Conceptualization, Supervision, Validation. **Christoph Buck:** Methodology, Investigation. **Erwin Fielt:** Writing – review & editing, Supervision, Visualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.giq.2022.101722.

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