Government Information Quarterly xxx (xxxx) xxx

Contents lists available at ScienceDirect

Government Information Quarterly

journal homepage: www.elsevier.com/locate/govinf

An attention-based view of AI assimilation in public sector organizations: The case of Saudi Arabia

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ARTICLE INFO

Keywords:
Artificial intelligence
Decision making
Attention-based view
Public sector

ABSTRACT

Artificial Intelligence (AI) has been suggested to have transformative potential for public sector organizations through enabling increased productivity and novel ways to deliver public services. In order to materialize the transformative potential of AI, public sector organizations need to successfully assimilate AI in their operational activities. However, AI assimilation in the public sector appears to be fragmented and lagging the private sector, and the phenomena has really limited attention from academic research community. To address this gap, we adopt the case study approach to explore three Saudi-Arabian public sector organizations and analyze the results using the attention-based view of the organization (ABV) as the theoretical lens. This study elucidates the challenges related AI assimilation in public sector in terms of how organizational attention is focused situated and distributed during the assimilation process. Five key challenges emerged from the cases studied, namely (i) misalignment between AI and management decision-making, (ii) tensions with linguistics and national culture, (iii) developing and implementing AI infrastructure, (iv) data integrity and sharing, and (v) ethical and governance concerns. The findings reveal a re-enforcing relationship between the situated attention and structural distribution of attention that can accelerate the successful assimilation of AI in public sector organizations.

1. Introduction

AI has the potential to transform the development and delivery of public sector services (OECD, 2020). The use of AI has been suggested to lead to an annual productivity increase 2% over the next 15 years (Wirtz, Weyerer, & Geyer, 2019) through better resource allocation (Jensen, 2020), automation of repetitive tasks (Eggers, Schatsky, & Viechnicki, 2017; Sun & Medaglia, 2019), decreased dependency on human decision-making (Eggers et al., 2017; Jakob & Krcmar, 2018), and addressing the limitations of the previous e-government initiatives (Barth & Arnold, 1999). Thus, it is hardly surprising that deployment of AI applications in sectors such as healthcare has increased significantly in public sector organizations (Davenport & Ronanki, 2018; Duan, Edwards, & Dwivedi, 2019; Misuraca, Van Noordt, & Boukli, 2020). Moreover, the use of AI has been suggested to reduce the administrative burden of public sector organizations (Androutsopoulou, Karacapilidisb, Loukisa, & Charalabidisa, 2019) for example through robotic automation of immigration processes will reduce the processing time and increase efficiency (Wirtz et al., 2019). Furthermore, since healthcare constitutes a major part of public spending, deployment of AI applications in healthcare and medical research has increased significantly in public sector organizations (Davenport & Ronanki, 2018; Duan et al., 2019; Misuraca et al., 2020).

AI technologies have diffused from academic research to become essential to the functioning of organizations across sectors (Pappas, Mikalef, Giannakos, Krogstie, & Lekakos, 2018) and to sustaining a competitive advantage (Berns et al., 2009; Davenport, 2018). Global spending on AI is predicted to be nearly $98 Billion in 2023, more than double what was spent in 2019 (International Data Corporation), and by 2025, nearly a quarter (24%) of global GDP will come from AI technologies (World Economic Forum, 2018).

In response to the anticipated economic and social benefits of AI, many high-profile AI-enabled digital transformation initiatives have been put forward by governments around the world (Butcher & Beridze, 2019; Jimenez-Gomez, Cano-Carrillo, & Lanas, 2020) including, Singapore (Tung & Rieck, 2005), New Zealand (Wirtz & Müller, 2019), Germany (Jakob & Krcmar, 2018), China (Allen, 2019), and the United Kingdom. For example, the government of China has spent $1.2 billion in AI development, and across Europe over €700 million has been invested in public-private partnerships (Wirtz et al., 2019). Moreover, as

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https://doi.org/10.1016/j.giq.2021.101617
Received 15 February 2021; Received in revised form 12 July 2021; Accepted 13 July 2021

a part of Horizon Europe activities, the Digital Europe Programme by the EU boost research and development (R&D) investments in AI among other digital technologies with 8.2 billion euros between 2021 and 2027 (European Commision, 2020). However, the assimilation of AI among public sector organizations appears to be fragmented and lagging the private sector (Mikalef, Boura, Lekakos, & Krogstie, 2019; Mikalef, Fjørtoft, and Torvatn, 2019; Mikhaylov et al., 2018; Zuiderwijk, Chen, & Salem, 2021). In the context of this study, assimilation is defined as an "organisational process that is set in motion when individual organization members first hear of an innovations development, that can lead to the acquisition of the innovation, and sometimes comes to fruition in the innovation's full acceptance, utilization, and institutionalization" (Meyer & Goes, 1988, p. 897).

The success of AI assimilation largely depends on effective integration of the new system with the existing system architecture and processes. This typically requires skills and resources beyond organizational boundaries (Butcher & Beridze, 2019; Donahue & Zeckhauser, 2011; Mikhaylov et al., 2018; Ransbotham, Gerbert, Reeves, Kiron, & Spira, 2018). Further, despite the extensive media coverage of AI initiatives in the public sector, there is a noticeable absence of empirical research that focuses on the challenges of AI assimilation in the context of the public sector (Sun & Medaglia, 2019; Wilson & Daugherty, 2018; Liu & Kim, 2018). The lack of empirical is so abysmal that Qian and Medaglia (2019, p.370) commented, "the scarcity of empirical studies on the impacts of AI in the public sector is particularly remarkable when we consider the unique nature of the problems of the public sector, as opposed to the private one. […] AI thus represents, in principle, an ideal technology to be applied to the public-sector context, where environmental settings are constantly changing, and pre-programming cannot account for all possible cases." Therefore, advancing knowledge through evidence-based insights and recommendations is critical (Cellan-Jones, 2014; Grandhi, Patwa, & Saleem, 2017; Mikalef, Boura, et al., 2019; Mikalef, Fjørtoft, and Torvatn, 2019; Reis, Santo, & Melão, 2019; Wilson & Daugherty, 2018) to support public sector organizations with their AI deployment initiatives.

To address this gap in knowledge, we elucidate the challenges in AI assimilation in public sector from the perspective of how organizational attention is focused situated and distributed during the assimilation process. To this end, use the attention-based view (ABV) of the organization (Ocasio, 1997; Ocasio & Joseph, 2005) as the theoretical lens through which to study the assimilation of AI in public sector organizations in Saudi Arabia. ABV acknowledges that the context in which cognition and action are situated determines which aspects of the environment (internal, external), key decision makers attend to and which opportunities to retain within the organization (Ocasio, 1997; Ocasio & Joseph, 2005). We adopt the definition of *attention* as proposed by Ocasio (1997), which encompasses the noticing, encoding, interpreting, and focusing of time and effort by organizational decision-makers to address challenges and seize opportunities. As a result, this study aims to answer the following question: *What challenges unfold in terms of organizational attention during the assimilation of AI in Saudi Arabian public sector organizations?*

This study contributes to research on AI and public sector organizations by advancing the understanding of focal concepts and their interrelationships (Ågerfalk, 2014). Specifically, the contribution of this study stems from its originality (Rowe, 2012; Corley & Gioia, 2011), by.

identifying key challenges and implications for practice that have not been reported in previous studies in public sector organizations.

The remainder of this paper is structured as follows. First, we provide context to this study by reviewing extant literature and introduce the attention-based view of organizations which is pertinent to understanding AI adoption in Saudi Arabian public sector organizations. Then the research methodology and data collection techniques are outlined. Next, key findings and analysis are presented. Followed by discussion, implications, and research agenda for future research and a conclusion.

2. Theoretical background

2.1. AI in public and private sector organizations

AI has been attributed to being the key driver of the so-called 4th industrial revolution (Brynjolfsson & McAfee, 2014), with much attention being focused on automation (Davenport & Ronanki, 2018), autonomous vehicles (Hengstler, Enkel, & Duelli, 2016), and fraud detection (Agrawal, Gans, & Goldfarb, 2017; Herrera, Figueroa, & Ramírez, 2018). AI is essentially a collection of technologies that combine large quantities of data, algorithms, and computing power in order to replicate the cognitive processes of a human, which include learning, reasoning, and self-correction (Andreasson & Stende, 2019; Mikalef, Boura, et al., 2019; Mikalef, Fjørtoft, and Torvatn, 2019; Pomerol, 1997). AI hold much promise to enhance or, if required, work as an alternate of human decision-making and actions (Mikhaylov et al., 2018; Wilson & Daugherty, 2018), improve operational efficiency, increase cost reduction, as well as new products using AI-based cognitive technology (Agrawal et al., 2017; Davenport & Ronanki, 2018; Thierer, Castillo O'Sullivan, & Russel, 2017; Zheng et al., 2018). AI has been claimed to convey significant transformative potential across the public and private sectors, ranging from reinventing business models to redesigning the customer experience to decision-making (Duan et al., 2019; Iglesias, Markovic, & Rialp, 2019) to changing the nature and the future of work (Dwivedi et al., 2019; Manyika et al., 2017; Schwartz, Hagel, Wool, & Monahan, 2019).

Governments are increasingly seeking ways to utilize AI across a wide range of public sector activities, including military, surveillance, healthcare services, medical research, transport, education, and emergency response (Allen, 2019; Wirtz & Müller, 2019; Wang & Lo, 2016; Misuraca et al., 2020; Sun & Medaglia, 2019). For example, AI-powered chatbots have been deployed to improve communication between governments and citizens and to help citizens to make decisions in various industries such as banking, telecommunications, and retail (Androutsopoulou et al., 2019; Park, 2017).

Despite the interest in AI by key decision-makers across the public sector, several environmental challenges to its assimilation in the context of the public sector have been reported, such as the opinion of citizens, which leads towards the perceived pressure of society (Desouza, Dawson, & Chenok, 2020; Schaefer, Kret, Ylinen, Mikalef, & Niehaves, 2021), and political concerns about the threat to national security (Sun & Medaglia, 2019). The assimilation of AI in the public sector is also hampered by the lack of public-private collaboration, due to the different organizational cultures of both sectors (Chen & Lee, 2018; Mikhaylov et al., 2018; Saz-Carranza & Longo, 2012). Hence, understanding the attention-based challenges during the assimilation of AI in public sector organizations in Saudi Arabia is pertinent to this study.

2.2. Attention-based view of the organization

We adopt the attention-based view (ABV) of the organization as the theoretical lens through which to study the assimilation of AI in public sector organizations in Saudi Arabia. ABV allocates the role of attentional orientation on the issue's decision-makers consider their time and effort on organizational/managerial attention (Ocasio, 1997, 2011). 'Attention' is a term in organizational science with a long and rich wide-ranging history since it was introduced as a central organizing concept by Herbert A. Simon (Simon, 1947) and subsequently became organization theory (March & Simon, 1958). March and his colleagues continued to focus on attention distribution as organizational decision-making (March, 1988). ABV of the organization (Ocasio, 1997) was put forward to explain an organizations' strategic decision-making and adaptation. A unique contribution of ABV is that 'attention' is used to encompass, note, encode, interpret, and focus time and effort by the organization's decision-makers on both issues and answers (Ocasio,

Table 1
Principles of ABV.

Principle	Description (Ocasio, 1997, p. 1)	Relevance in this study
Focus of attention	What decision-makers do depend on what issues and answers they focus their attention on?	Making sense of how organizational attention is directly related to AI assimilation.
Situated attention	What issues and answers decision-makers focus on and what they do, depends on the context or situation they find themselves in.	In situated attention, the trigger for the decision to solve the emerging challenges and obstacles can be initiated under the organization's leadership itself (internal). For example, misalignment between AI decision-making and management decision-making, administrative integration, ambiguity, and awareness about AI. Issues that managers have found themselves in this situation and can solve it within the organization itself.
Structural distribution of attention	What context or situation decision-makers find themselves in, and how they attend to it, depends on how the firm's rules, resources, and social relationships regulate and control the distribution and allocation of issues, answers, and decision-makers into specific activities, communications, and procedures.	Structural distribution of attention that the government entities await concerted efforts between other parties to develop these obstacles. For instance, data policy and legislation should be solved with external decision-making like another government entity (i.e., AI adoption guidelines challenges may come across different parties for written procedures or recommendations for governing the system).

1997). From the ABV perspective, 'issues' refer to the available repertoire of categories for making sense of the environment: problems, opportunities, and threats, and 'answers' refer the available repertoire of action alternatives: proposals, routines, projects, programs, and procedures (Ocasio, 1997, p.3).

Through the lens of ABV, organizations are viewed as a range of groups for making sense of the environment and its threats, problems, and opportunities, whereas the latter is the available range of actions, and its routines, proposals, procedures, programs, and projects can be derived from a particular organizational context that a decision-maker might find themselves in (Ocasio, 1997; Ocasio, 2011; Ocasio & Joseph, 2005). More recently, ABV has been increasingly being applied as a theoretical lens to study various aspects of strategy-related phenomena, including theoretical research (Barnett, 2008; Ocasio & Joseph, 2005), empirical studies (Joseph & Ocasio, 2012; Ketokivi & Castaner, 2004; Mäntymäki, Hyrynsalmi, & Koskenvoima, 2019; Rerup, 2009; Sullivan, 2010), emerging strategy formulation and decision making (Ocasio & Joseph, 2008; Ocasio, Laamanen, & Vaara, 2018), adaption and change in decision making (Ocasio et al., 2018; Ocasio & Joseph, 2018), and environment complexity (Guarana & Hernandez, 2015; Oliver, Calvard, & Potočnik, 2017). The significance of governance channels for directing strategy construction has been acknowledged in ABV literature (Joseph & Ocasio, 2012; Vuori & Huy, 2016). The attentional process of a group or individual decision-makers is divided throughout the various functions that occur in an organization, with various foci of attention in every local activity, communication, or procedure (Ocasio, 1997). The organization's governance channels are used to link the available processes and capabilities with its issues and lead the way for an organization's strategy (Ocasio & Joseph, 2005). In turn, these processes and capabilities can be termed as an organization's ability to combine, develop, and reconfigure external and internal competencies to respond to an environment that changes rapidly (Eisenhardt & Martin, 2000; Teece, Pisano, & Shuen, 1997). From the ABV perspective, where decision-makers focus their attention is context and situation-specific (Ocasio, 1997). In summary, ABV is based on three inter-related principles (see Table 1).

2.3. Innovation adoption & assimilation theories

Several researchers have proposed various theories and models that explain innovation adoption and assimilation which has advanced our understanding about factors that influence user acceptance of a specific innovation (Abbasi, Tarhini, Elyas, & Shah, 2015; Gangwar, Date, & Raoot, 2014; Liu, Min, & Ji, 2008; Williams, Rana, & Dwivedi, 2015). The traditional innovation adoption models, namely, Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975); Technology Acceptance Model (TAM) (Davis, 1989); Technology Organization Environment (TOE) Framework (Tornatzky & Fleischer, 1990); Diffusion of Innovation Theory (DOI) (Rogers, 1995), and Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh, Morris, Davis, & Davis, 2003) have received considerable attention in the IS literature (Gallivan, 2001). These models focus on the adoption of innovations by individuals making autonomous choices about whether to adopt personal use of innovations. However, in the organizational context, exists an 'authority-based contingent adoption of innovations' (Gallivan, 2001, p. 59) whereby individuals simply cannot choose to adopt a specific innovation. It well established that an innovation may be introduced amid much hype and be widely acquired, but then fail to be thoroughly deployed among acquiring organizations (Fichman & Kemerer, 1999).

To offset the limitations of traditional individual adoption models, Gallivan (2001) integrates the six-stage assimilation process model (cf. Cooper & Zmud, 1990) with some constructs from traditional individual adoption frameworks. Gallivan (2001) posits that innovation adoption in the context of organizations is a two-stage process, starting with the 'primary adoption' (i.e., an organizational-level decision to adopt an innovation), followed by the 'secondary adoption' which includes individual adoption and six organizational assimilation stages. The secondary adoption stage essentially outlines the organizational processes and norms that lead to organizational assimilation and secondary adoption. These specific norms can differ and vary for a specific adoption and innovation context (ibid). Subjective norms tend to shape the beliefs of potential adopters regarding why and when to adopt a specific innovation and how much effort to invest in it. Facilitating conditions (i.e., organizational culture, attributes of the innovations, nature of the work) refer to factors that can cause the implementation to take place or not. Once the secondary adoption process occurs, the assimilation stage is then used to described how deeply the innovation penetrates the adopting organization (ibid*).*

The innovation assimilation framework has been widely used by IS researchers to advance knowledge since it was first proposed by proposed by Gallivan (2001), including information technology (IT) and web technologies (Baird, Davidson, & Mathiassen, 2017; Chatterjee, Grewal, & Sambamurthy, 2002; Manuel Maqueira, Moyano-Fuentes, & Bruque, 2019; Wright, Roberts, & Wilson, 2017), technological innovation in the contexts of small businesses and large firms (Narvekar & Jain, 2006), migrating towards e-businesses or online businesses (Zhu, Kraemer, & Xu, 2006), e-procurement systems (Rai, Brown, & Tang, 2009), enterprise resource planning systems (Bajwa, Garcia, & Mooney, 2004; Shao, Feng, & Hu, 2017), cloud computing (Ooi, Lee, Tan, Hew, & Hew, 2018; Wang, Xue, Liang, Wang, & Ge, 2019), big data (Bharati & Chaudhury, 2019; Weibl & Hess, 2018), and social media (Cao, Ajjan, Hong, & Le, 2018).

We apply the innovation assimilation framework proposed by Gallivan (2001) to identify the phase of adoption for each case studied. While all three cases were at the secondary phase of adoption, they differed in terms of maturity.

Table 2
Description of the cases.

	Case Study 1	Case Study 2	Case Study 3
Established	2019	1998	1957
COFOG	F1. General public service	F9. Education	F4. Economic affairs
Type of Organization	A government authority	A public university	A semi-state-owned financial institution
Organization activity	Responsible for the development and assimilation of AI-based public services.	Design and delivery of degree programmes that are aligned with the 2030 vision and goals of Saudi Arabia.	Core business is provision of Islamic banking services to citizens and funding major infrastructure projects.
AI projects	In partnership with the Ministry of Health and the Ministry of Telecommunications and IT, two AI-based systems were deployed to manage the response to the Covid-19. The first is *Tawakkalna*, a machine learning algorithm that identifies regions that need to be designated as partial or full lockdown zone. The second is *Tabaud*, a tracking software based on geospatial data analysis that predicts high risk infection zones and the number of people that could become Covid positive (Tabaud, 2020).	The university has dedicated AI department that is responsible for coordinating the assimilation of AI-based system that automates more than 137 administrative tasks and teaching and learning activities (e.g., evaluating and predicting student performance, monitoring learning outcomes, predicting students learning style), as well as a recommendation system for over 70,000 students (Alwalidi & Lefrere, 2010).	Established the first national *innovation lab* to leverage AI applications for the digital transformation of the bank's national infrastructure, and design and delivery of innovative banking services to society (Maaal, 2014).

Case study 1 was the most advanced case as it was considered to be at the post-adoption phase and at final phase of assimilation (i.e., Infusion), whereby increased organizational effectiveness is obtained by using the AI application in a more comprehensive and integrated manner to support higher level aspects of work.

Case study 2 was the least advanced case as it had completed only two phases of adoption (e.g., pre-adoption, and adoption) which consists of two phases of assimilation (e.g., Initiation, Adoption), whereby managers found a match between AI and its application in the organization (Initiation) and had made a decision to invest resources to accommodate the implementation effort required for the AI initiative.

Case study 3 was considered to be at the post-adoption phase as it completed the preadoption and adoption phases, as well as three phases of assimilation (e.g., adaptation, acceptance, and routinization), whereby the AI technology has been adapted and implemented, procedures developed, and employees are actively encouraged and supported to use the technology as part of their daily activities.

Table 3
Interviewee profiles.

Case Study	Interviewee Code	Interviewee job title	Team	Years of relevant work experience
1	SA01	Project Manager and Data Scientist	Management	7
	SA02	AI advisor	Team	4
	SA03	CEO of Confidential Product & Google CDC Leader	Management	6
	SA04	Senior Data Scientist	Management	22
	SA05	Project Manager and Researcher	Management	18
	SA06	Executive Assistant	Team	3
2	UI01	Director of Centre for AI	Management	16
	UI02	Dean of IT	Management	9
	UI03	Vice Dean of IT	Management	11
	UI04	*E*-learning Department and IT project	Team	7
3	PS01	Internal Auditor and IT Advisor	Management	7
	PS02	Manager	Management	8
	PS03	IT Consultant	Team	10
	PS04	Loan Advisor	Team	6

3. Research methodology

We adopt a multiple case study involving three public sector organizations in Saudi Arabia (Klein & Myers, 1999; Orlikowski & Baroudi, 1991; Walsham, 1993). The case study method was chosen because it is suited to "understanding of the context of the information system, and the process whereby the information system influences and is influenced by the context" (Walsham, 1993, pp. 4–5). The case study approach is also appropriate to understanding a phenomenon that lacks empirical evidence (Benbasat, Goldstein, & Mead, 1987; Eisenhardt, 1989; Stake, 1995) and to extend the theoretical underpinning (Stuart, McCutcheon, Handfield, McLachlin, & Samson, 2002; Benbasat et al., 1987). In this study, documentation, archival records, and semi structured interviews were used as sources of data collection and triangulation (Eisenhardt, 1989; Yin, 2009). The cases studied were purposefully selected for three reasons. First, the cases are exemplar cases as they are the first public sector organizations to pioneer AI applications in Saudi Arabia. Second, each case was at a different stage of assimilating AI applications, which provided rich insights into the challenges. Third, a member of the research team had direct access to the cases, which provided context to the reported challenges.

3.1. Research context

In 2016, the Government of Saudi Arabia launched the Vision 2030 framework that focused on the digital transformation of key public sector services (i.e., education, healthcare, financial services). Vision 2030 identifies a range of institutions and investment in AI infrastructure and other digital technologies (i.e., IoT) (Filho, 2017). The Kingdom of Saudi Arabia is recognized by the European Centre of Digital Competitiveness as a leading economy in terms of digital transformation over the last three years (Abul-Enein, 2020). For instance, in September 2019, the leader, King Salman Bin Abdelaziz, gave a decree to set up a "*Saudi Data and Artificial Intelligence Authority (SDAIA)*". The proposal would see the country officially join the digital world, especially since Saudi Arabia's digital advancement goal was part of its Vision 2030 framework. Notably, the reform can be perceived as a move to accelerate AI and digitization, which are key enablers of achieving the nation's 2030 goals (Nabbout, 2019). Indeed, the assimilation of AI in the context of Saudi Arabia provides research opportunities to advance understanding into the concepts surrounding AI (ibid).

3.2. Case descriptions

In this study, the three public sector organizations are categorized by its functions of government (see Table 2) which is based on the *Classification of Functions of Government* (COFOG) framework. The 10 categories (F1. General public service, F2. Public order and safety, F3. Defence, F4. Economic affairs; F5. Environmental protection, F6.

Table 4
Summary of codes used in data analysis.

Code	Description	Interview Quotes
Administrative Integration	Cooperation at the administrative level	"*There is no administrative integration with each other, as each department has a different system.*" (UI01).
AI Ambiguity and Awareness	At the level of problem-solving desire or AI awareness	"*Some of the organizations misunderstanding the AI concept, for example, when they face some problems, they asked for AI application to be implemented, while the problem could only relate to some data analysis and visualization dashboard only*". (SA06)
KPI (key performance indicator)	AI Adoption performance measurement.	"*I have noticed that decision-maker who is interested in AI are the ones with passion and interest in AI. It is not a matter of innovation and development as well as it is an individuals' initiative. Hence, we need to use a key performance index for using AI.*" (SA02)
Language	Some AI tools does not support Arabic Language or existing tools not as accurate as with Latin languages	"*There is an inadequacy of the Arabic language processing tools*". (UI02)
Gender	Separated male and female departments at the same organization	"*There is miscommunicating between technical teams, female sections, male team and decision-making council.*" (UI03)
Resistance to emerging AI Technology	Leaders/ employees either are fear AI failure or, losing their job or being replaced.	"*There are some traditional people who don't like the machine to intervene in the working environment. They accept only paper decisions and letters.*" (UI04)
AI Infrastructure	How to build a system for AI adoption	"*Most people focus on AI, the top of the hierarchy of infrastructure, while the quality of Data, in particular the need for clean and data fidelity, little attention is typically paid to Data engineering. AI is going to build on top of weak and inaccurate data, which leads to inaccurate performance.*" (SA01)
Blackbox Tools	Dealing with AI applications without knowing their details and the importance of adopting them in the organization.	"*We need to understand AI tools in details do not deal with it like a Blackbox.*" (SA01)
Data Ownership	data importance, sharing and accessing	"*At a most public organization, in a general point of view, the data maturity is not fully available at this moment in most government departments; part of this issue is data ownership.*" (UI01)
Experience Scarcity	Lack of data scientist expertise	"*In addition to that the lack of specialists in the Big Data field. I expect that new jobs will be created.*" (UI01)
Data Quality	Management and control of data quality	"*Data quality management in the public sector, Hierarchal management to divide into departments considering data collecting, auditing, cleaning, and quality management. These data processing challenges are still remaining which needs years to solve it*". (SA01)
Lack of Legislation	AI and data governance	"The *ethical issues could be divided into 2 categories; one is the AI going forward will replace FTEs and hence employment opportunities. This needs to be balanced through the right skilling of existing staff. Second, machine learning technologies may result in a breach of data privacy and humans' overall privacy. This needs to be balanced with the anonymization of data, which enhances data security.*" (PS02)
AI Guidelines	The general entity takes the responsibility of AI and Data governance to unite regulation-making policy	"*There are no ethical guidelines specifically related to AI until this moment. What kind of governance mechanisms do you have regarding the use of AI? There isn't governance in regard to AI until now.*" (PS01)
Risk and Security	Losing AI operation control	"*Another concern is security, if anyone breaches the system and changes the loan orders or the numbers approved by the system, no one will know about it. AI methods need more control.*" (PS04)
Data Governance	Data regulations and policy	"*Data are still collecting manually, no united database store system, no regulations on how to use it*" (SA01)

Housing and community amenities, F7. Health, F8. Recreation, culture, and religion, F9. Education, and F10. Social protection) are based on how governments segment their activities and direct their expenditure and management to achieve socio-economic objectives (OECD, 2011).

3.3. Data collection

To identify the key decision-makers involved in the AI projects at each of the cases studied, we employed 'snowball sampling' (Naderifar, Goli, & Ghaljaie, 2017; Noy, 2008). Snowball sampling is widely used in qualitative research in various disciplines as it enables the researcher to access interviewees through the contact information provided by other interviewees (Noy, 2008). This approach enabled us to identify and interview 15 key decision-makers with extensive industry experience and knowledge of AI (see Table 3). The semi-structured interviews (see Appendix A: Interview Guide) were conducted remotely using online meeting tools (e.g., Zoom, Microsoft Teams). The duration of interviews ranged between 40 and 60 min. Semi-structured interviews were used to obtain rich insights to the context of the three cases studied and the emergent challenges. Interviews were recorded and transcribed using Otter, an AI-based transcription software, proof-read and annotated. Notes were taken during the interviews. For the purpose of research rigor and anoymonity, a code (e.g., SA01) was assigned to each interviewee.

3.4. Data analysis

Analyzes of the data was guided by the Gioia method (Gioia, Corley, & Hamilton, 2013) as this method can extract novel insights by carefully investigating how different actors of an organizational process experience events (i.e., adoption of AI). The Gioia method also facilitates 'research rigor' (Gioia et al., 2013) as it enables inductive researchers to use systematic, conceptual, and analytical discipline, that can lead to findings that are credible. We began our analysis using open coding (Strauss & Corbin, 1997) and it required reading of the interviewee

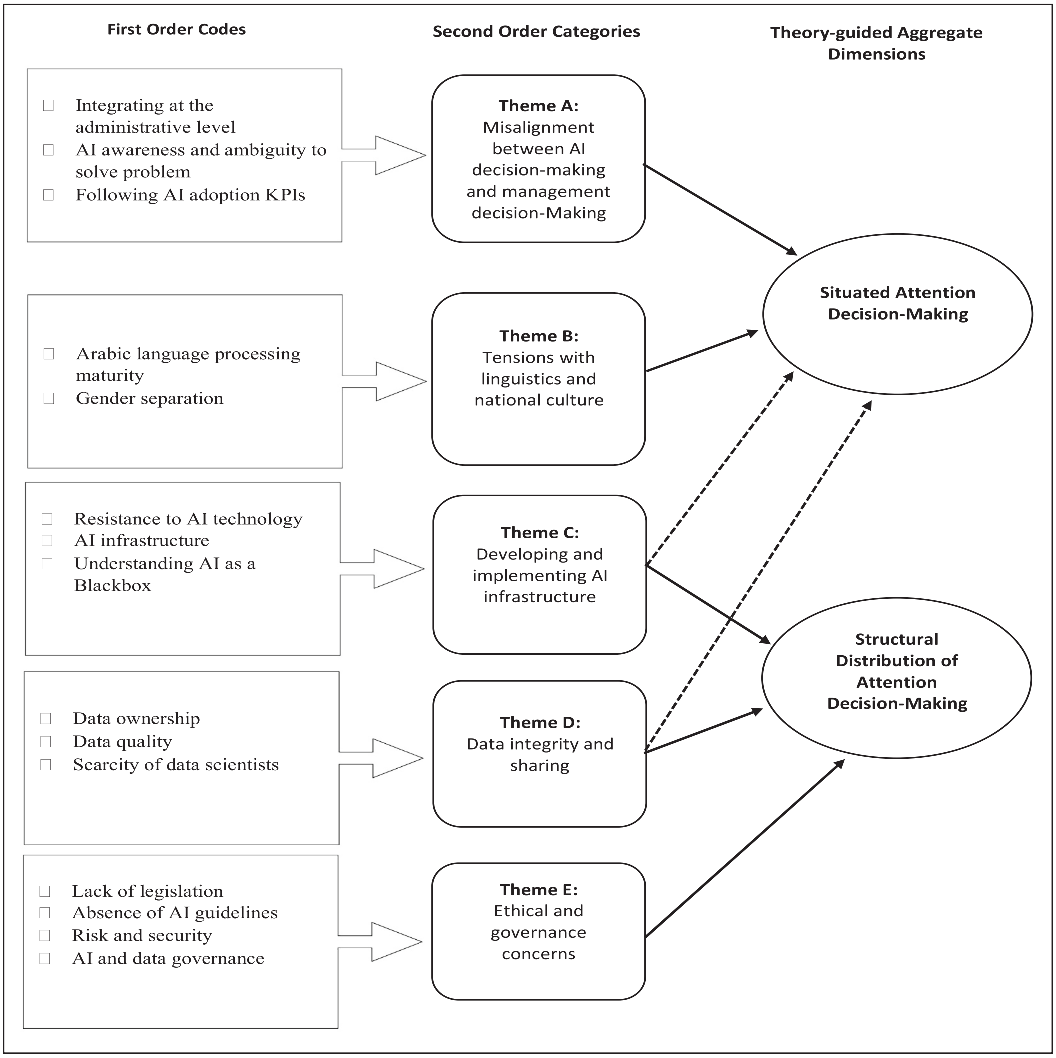

Fig. 1. The three stages of the analysis process employed in the research.

transcripts and marking codes for describing interview content. We used the research questions (see Appendix A) to guide the first round of coding which resulted in 27 emergent categories. The authors jointly studied these categories to identify similarities and differences (Strauss & Corbin, 1997) which resulted in 15 categories as a first-order code description. After establishing the first-order codes, we moved forward to combine codes into second-order themes representing the challenges in AI assimilation. In this stage of the analysis, we developed categories that would assist in describing the phenomena under observation. In this stage, the categorized challenges emerge as second-order categories; these categories and their interdependence essentially became tentative answers to our research question: *What attention-based challenges emerge during the assimilation of AI in Saudi Arabian public sector organizations?* Following this iterative and rigorous process of formulating and analyzing the themes, we reached the point of theoretical saturation (Glaser & Strauss, 1967). Theoretical saturation means that the incoming data do not show new information for the purpose of the research aim as repetitive comments are provided by interviewees (Guest, Namey, & Chen, 2020; Merriam, 2009). Table 4 provides a summary of the 15 codes and 5 key attention-based challenges that emerged from the data analysis.

We took several measures to ensure a clear chain of evidence from data collection to our interpretation of the data and findings. First, the Gioia method is provides a rigorous analytical approach that guided data collection and analysis. This in general reinforces the research rigor and thus increases the credibility of the findings and their interpretations findings (Gioia et al., 2013). Second, we followed the well-established guidelines for conducting qualitative case research by (cf. Kelliher, 2011; Stake, 1995; Yin, 2009) to ensure the trustworthiness of the study, in terms of reaching theoretical saturation, credibility, generalizability (Robson, 2002; Suter, 2014). In terms of validation, our research depends on presenting rich descriptive data (Stake, 1995). Finally, the interviews involved key decision-makers at each case studied, meaning we were dealing with knowledgeable agents (Gioia et al., 2013).

4. Key findings

Whilst the principle of focus of attention states that decision-making processes are guided by selective attention, it means managers pay to issues at any given time, where individual characteristics drive it. However, managers at the same organization may pay their attention to different issues, depending on their contextual interests, understating, or if it is not in line with prior experience (Barreto & Patient, 2013; Ocasio, 1997; Shepherd, McMullen, & S., & Ocasio, W., 2017). On the other hand, we emphasize more on two other principles, situated attention and structural distribution of attention, because those managers and key decision-makers who found themselves in this situation responding to what was imposed on them by the government and its orientation towards the assimilation of AI. Therefore, personal, relational, and situational characteristics all influence the allocation of scarce and restricted managerial attentional resources.

To that end, two aggregate themes 1) *Situated Attention Decision-Making,* and 2) *Structural Distribution of Attention Decision-Making,* portraying different foci of attention in challenges regarding AI assimilation emerged because of the third stage of the data analysis. The first aggregate theme, *Situated Attention Decision-Making,* refers to a single organization can fix the challenge internally that means each entity could make decisions and solve any related issues internally within the organization manages itself. The second aggregate theme, *Structural Distribution of Attention Decision-Making,* means that the decision-making should be resolved with a high-level committee, government, or cross-organizational decision making, which means the decision to solve related challenges will require cross collaborations with external entities. In summary, understanding AI adoption technology, identifying its implementation obstacles, and creating internal and external organizational collaboration are critical for public decision-makers to overcome its adverse impact and spread AI benefits. The recently established Saudi Data and Artificial Intelligence Authority (SADIA) is responsible for managing the AI initiatives in the public sector. In the third stage of the analysis process, we incorporated the ABV perspective into the analysis and specifically looked at how attention manifests itself in the categories identified in the previous stage. This led to the emergence of two theory-guided aggregate dimensions through which we study the challenges of AI adoption for decision maker's (Ocasio, 1997). Collectively, the first-order codes, second-order categories and the third aggregate themes constitute the data structure (Gioia et al., 2013). The data structure allows configuring the data into a more sensible and visual form, and it gives a graphically illustrative projection to how a progression from raw data to themes has been carried out. Altogether this reinforces the rigor of qualitative research (Pratt, 2008; Tracy, 2010). The three stages of the analysis process are summarized in Fig. 1. The five key challenges that emerged from the cases studied are presented below, namely, (i) misalignment between AI decision-making and management decision-making, (ii) tensions with linguistics and national culture, (iii) developing and implementing AI infrastructure, (iv) data integrity and sharing, and (v) ethical and governance concerns.

4.1. Challenge 1: Misalignment between AI decision-making and management decision-making

Understandably, technology adoption would face managerial challenges. More specifically, in the adoption of AI, some recent studies state that there is a lack of clear leadership with a vision for integrating AI solutions in the administrative processes (Dwivedi et al., 2019; Meijer, 2015; Sun & Medaglia, 2019). Further investigation is needed for developing collaborative leadership and management support (Desouza, 2018). Understanding AI applications is a key challenge at the organizational leadership level. In addition, the process of implementing a new system in the organization is a critical matter when this organization employed the new complex technology under governmental pressure in our case studies. Moreover, controlling the natural worker's resistance to changes can slow or even fail to implement an important key. For instance, the lack of AI awareness is demonstrated in the following quotation:

> *"The decision-maker only wants the plug and play techniques." (UI02).*

Interviewees also discussed whether any of these challenges were present at the administration level. For this reason, the interviewees emphasized the need to launch awareness initiatives for senior management to understand how AI can help develop performance and achieving a high accuracy rate. It might be an effective way to study the group's or individuals' readiness to make sure how the employees understand the AI importance as well as an open discussion platform for issues and solutions that consider being solved by AI. The training course, talks, or coaching might be needed to successfully implement the AI in the organization to achieve the goals and vision within the organization.

> *"The decision-maker or the manager does not always consider the organization's vision about AI and whether applying it would be effective or not, also how ready are the organization and employee are." (UI03).*

4.2. Challenge 2: Tensions with linguistics and national culture

The interviewees largely viewed the Arabic language processing tools developed as a requirement. The Arabic language processing tools are not mature when compared to other languages. It still faces several difficulties such as scarcity of Arabic language resources, the plurality of Arabic dialects, language ambiguity, semantic pattern recognitions, the shape of the letter itself varies depending on its position within the word, also the limited scientific research in the field of Arabic language processing. These challenges make the Arabic Language processing a unique case for AI technologies adaptation. Technical efforts are needed at several levels to solve these obstacles to engage with AI technologies.

According to the One World-Nations Online Project (One World-Nations Online Project, 2020), the Arabic Language is the official language of the 26 countries. In addition, the Arabic language writes right-to-left direction, and it can be categorized into three forms: Classical, Modern Standard, and Colloquial Arabic accents. However, these dialects differ in their writing and "grammar" from Classical Arabic. Thus, artificial intelligence models that have been trained on formal language resources might fail to deal with texts written in dialect. The interviewees consistently claimed that the Arabic language processing tools shortage was so evident that there is a need for concerted efforts to solve this dilemma for all organizations.

> *"The Arabic Language is un-matured in terms of tools and libraries. It takes years. Even though, if we use a tool from IBM or else, the accuracy is very low. There is a gap between theories and practices if we take a daily base operation. There are few attempts, but they focus on a number of NLP tasks like a lexical dictionary, accent speech corpus, etc." (SA05).*

Saudi Arabia is considered the most genuinely gender-segregated nation (Baki, 2004). Most education systems and some authorities are currently still clinging to the idea of segregation between the genders. However, there is a social change to accept both gender homogeny in work and business, especially for a modern and recently established organization to be compatible with the vision of the Kingdom 2030. An example of this is SADAIA, the leading authority in the field of AI in the Kingdom. In our study, the interviewee explicitly highlighted that the communications might be affected due to gender differences. She explained that the division between the men and women sections makes it difficult to participate and present suggestions and solutions and that it is almost limited to presenting them in the organization's official meetings.

> *"There is miscommunicating between technical teams, female sections, male team and decision-making council." (UI03).*

4.3. Challenge 3: Developing and implementing AI infrastructure

Interviewees commented that AI infrastructure required several key issues i.e., big data collection, tools management, AI experts, AI development and maintenance, and increasing cost of education that needed to be addressed (Bughin et al., 2017; Holdren & Smith, 2016; Kankanhalli, Charalabidis, & Mellouli, 2019; Roberts, 2017). AI Infrastructure development is a key factor in adopting AI technologies in the public sector. These structural environments start from hardware, software, communications, etc. Examples of these platforms are data management, AI commercial and open-source tools, AI and Data governance, data sharing policy, etc. Building on a solid foundation will contribute to AI adoption achievement. Some interviewees raised concerns about the infrastructure of AI and its implementation, as an informant is quoted here:

"A large number of data, we have 60 thousand students, and every student has dedicated data, this huge number needs to be managed efficiently also need a well technological infrastructure must be established (Big Data technologies)." (UI01).

Understanding AI benefits is considered a main driven factor to accept it in society (Hameed, Ten, Thomsen, & Xiaodong, 2016; Petit, 2018). This view was echoed by another interviewee who believed that there is resistance from some people in leadership roles and employees due to a fear of losing their job or being replaced by AI. Furthermore, humans are used to the traditional systems and do not like machine intervention very much.

"There are some traditional people here in the organisation who don't like AI to intervene in the working environment. They accept only paper-based decisions and recommendations." (UI04).

Public sector organizations must cultivate awareness of what AI is, not only as a term, but also its importance, tools, applications, and how it can develop their organization. At the level of problem-solving desire, AI awareness is highly required in the first place. It is being asked to implement these tools. Some of the entities are misunderstanding the AI concept due to some of these tools' ambiguity.

"Another challenge is what type of AI the public sector is looking for (some entities don't need, or they don't have a problem)." (SA02).

4.4. Challenge 4: data integrity and sharing

While AI depends on the data, a significant barrier for implementing AI in public sectors heavily relies on data quality and shortages. These obstacles could be poorly structured data (Koutroumpis & Leiponen, 2013), absence of data standardization, and access difficulties (Christodoulou, Decker, DoukaCharalampia, & Peristeras, 2018; Sun & Medaglia, 2019). In the context of the public sector, various activities in relation to data needed to be considered, such as data management strategies (Chen & Zhang, 2014; Janssen, van der Voort, & Wahyudi, 2017; Kim, Trimi, & Chung, 2014).

Data is termed as the most valuable possession; that is why against the code accessing and sharing, an interviewee can be quoted here:

"Decision maker/leaders hesitate to share data because whether they are not aware of the importance of data or they are worried about taking responsibility for data in case of legal reasons." (SA02).

Interviewees also acknowledged that ambiguity leading to ignorance constant refusal to share data from who owns the data. Sharing and accessing the data are still the main concerns in the public sector. Data sharing agreements must be related to data security and privacy processes related to the disclosure of sensitive information to the public, which is considered an ethical challenge (Desouza, 2018).

"At a most public organization here in Saudi, in a general point of view, the data maturity is not fully available at this moment in most government departments, part of this issue is data ownership. Most leaders deny sharing it." (UI01).

4.5. Challenge 5: Ethical and governance concerns

AI and Data ethics can be concerned in terms of different aspects. These concerns deal with related data ethics like shared data, accuracy, completeness, and privacy concerns. On the other hand, it could be related to AI regularization, for instance, trust towards AI-based decisions, lack of transparency, bias, and fairness (Engstrom, Ho, Sharkey, & Cuéllar, 2020; Dwivedi et al., 2019; Sun & Medaglia, 2019; Kankanhalli et al., 2019; Wirtz & Müller, 2019; de Sousa, de Melo, Bermejo, Farias, & Gomes, 2019; Mikhaylov et al., 2018; Veale, Van Kleek, & Binns, 2018). The data governance raises data quality which expresses the measures taken within the public sector or entity. It aims to regulate data publishing and consumption by committing to the institution's laws and the existing legislation in the country. A concerned interviewee can identify the issues that suggest either the ethical nature of the predictions or the end outcomes or their direct and indirect effect on people, for instance, quoted here:

"One of the ethical issues raised by AI is lay-off. Employee's fear losing their jobs or replacing employees with robots, so it is hard to adapt to the new machine where they used to deal with a human being." (PS01).

Most interviewees unanimously regarded ethical issues as the biggest obstacle to the organization-wide adoption of AI and that national regulation on the adoption and governance of AI and the associated data. For example, one interviewee stated that.

"Data are still collecting manually, no united database store system, no regulations on how to use it" (SA01).

A similar view was shared by another interviewee, relating to AI governance.

"Until now, there are no legislative controls regarding artificial intelligence." (UI02).

Interestingly, while there was a consensus on the significance and governance of AI and data, the interviewees also discussed how scaling AI adoption makes it more challenging to control AI guidelines and related issues.

"Data needs to formulate rules and clear structures for data management. Data quality management in the public sector, Hierarchal management to divide into departments considering data collecting, auditing, cleaning, and quality management. These data processing challenges are remaining, which needs years to solve it." (SA01).

In summary, the five key challenges that emerged from the cases studied are, (i) misalignment between AI decision-making and management decision-making, (ii) tensions with linguistics and national culture, (iii) developing and implementing AI infrastructure, (iv) data integrity and sharing, and (v) ethical and governance concerns.

5. Discussion, implications, and future research

In this study, we focused on the challenges of AI in the context of public sector organizations in Saudi Arabia, which is an inherently complex and socially embedded activity. We introduce a theoretical decision-making pattern based on ABV to derive contextual insights from public sector organizations in Saudi Arabia. By using the principles of 'situated attention' and 'structural distribution of attention' (Ocasio, 1997) our study highlights that the key decision-makers play a crucial role in directing organizational attention, depending on the specific context, especially with a new complex technology such as AI. With situated attention and structural distribution of attention decision-making dimensions in the third stage, the trigger for the decision to solve these challenges and obstacles can be started situated process under the organization's leadership itself (internal). Where structural distribution of attention that the government entities await concerted efforts between other parties to develop these obstacles. For instance, data policy and legislation should be solved with external decision-making like another government entity in our study SADAIA who takes the lead.

In theme A, 'administrative integration' in the existing organization can be seen in the situated dimension where the decision-makers focus on a particular context or situation they find themselves in. Within the same theme, KPI should be used based on which a system is evaluated, and here it means that the adoption will initially be evaluated based on key performance indicators within the organization itself. On the other aggregate dimension, e.g., structural distribution of attention decision-making, the decision-maker attends regulating and managing the distribution and allocation challenges. For instance, AI adoption guidelines in theme E may come across different parties for written procedures or recommendations for governing the system. Another example is data and AI governance in theme E which means that data collection and other ethical issues are used in the subsequent decision processing and how each entity behaves.

By adopting the ABV lens, we advance knowledge by providing an empirical investigation of how existing attentional engagement can facilitate an organization's ability to address challenges in the context of public sector organizations in Saudi Arabia. Our study makes a methodological contribution by linking attention processing to organizational tensions in solving of technological issue focus (cf. Ocasio & Joseph, 2005, 2018). An enhanced understanding of the implications of attention configuration (Joseph & Ocasio, 2012; Wilson & Joseph, 2015) and the insights generated from this study provide implications in how AI is utilized in the decision-making process for future research agendas along these lines. Finally, we summarize our results into expanded practical guidelines. Thus, our research could facilitate the speed and accuracy of decision-makers' perception and action to tackle these challenges, dependent on the characteristics of the issues and procedural attention (Ocasio, 1997).

Our study provides unique understanding of how conceptual dimensions of ABV serve as a mechanism for specializing attention and reflect both a managerial focus on challenges. *First,* from the ABV perspective, attention to the AI implementation activities underlying considering the key challenges emphasizes consistency in decision processing across actions, issues, and opportunity, and the coordination of external and internal parties involved. Therefore, the study of AI assimilation should adopt a long-term lens to observe if AI applications are in fact still in use after a certain time and better understand the consequences of its adoption (Bailey & Barley, 2019). *Second,* by understanding the relationship between attention and complex technology implementation such as AI demands that we understand how attention is distributed in connection with the decision process to identify challenges, attention processing, and communicating between the governmental firms involved (Ocasio, 2011). Towards this view, we consider the relationship between attention processing and the AI implementation-related issues, challenges in the long run for decision-making outcomes. *Third,* we follow Ocasio (1997) in defining attention as dimensional focusing of time and effort by organizational decision-makers on challenges. Doing so provides guidelines for practitioners in identifying a relevant organizational configuration in this regard (Ocasio, 1997). From an ABV point of view, more important than managerial processing capacity are the challenges that decision-makers perceive to be critical and on which their attention is focused at a particular time and place. Coherence throughout the organization's channels may avoid ambiguities regarding the interpretation of challenges and provide a consistent understanding AI of what solutions should look like (Kaplan & Tripsas, 2008; Rerup, 2009). In addition, key performance indicators (KPIs) may emerge as an essential performance indicator that represents a particular characteristic measured to assess attentional processing (Parmenter, 2015).

5.1. Contributions to research

The contribution of this study stems from its originality and utility (Rowe, 2012; Corley & Gioia, 2011) and advancing the understanding of the focal concepts and their interrelationships (Ågerfalk, 2014). First, the most salient contribution of this research is the use of ABV as a theoretical lens to study AI assimilation in the context of public sector organizations in Saudi Arabia. This is an important contribution as this study supports research calls to address the paucity of research on AI in public sector organizations (Sun & Medaglia, 2019; Wilson & Daugherty, 2018). Second, ABV enabled us to illuminate key challenges in adoption and implementation of AI in its natural context where it is intended to be used. Third, ABV advances knowledge by providing an empirical investigation of how existing attentional engagement can facilitate an organization's ability to address challenges in the context of public sector organizations in Saudi Arabia. Further, the insights obtained from this study provide implications in how AI is utilized in the decision-making process.

As our study builds upon extant AI literature, it contributes to the tradition of accumulative building of knowledge (cf. Metcalfe, 2004; Weick, 1989). This research builds on a cumulative body of knowledge related to the adoption and deployment of AI in the public sector, by rigorously identifying two theory-guided aggregate dimensions (e.g., situated attention decision making, and structural distribution of attention decision making) through which we study the challenges of AI adoption for decision maker's (Ocasio, 1997). The research extends previous studies by demonstrating that there is a reenforcing relationship between the situated attention and structural distribution of attention that can accelerate the successful assimilation of AI in public sector organizations. This is an important finding that has implications for research as much of the existing research on AI and public sector organizations focus on the technological aspects of AI applications, without a consideration of public administration models that reveals the implications for governance of the administrative state (Sharma, Yadav, & Chopra, 2020).

5.2. Implications for practice

Our study offers actionable practical insights for management and other key decision-makers in public sector organizations. It provides a first step towards a more systematic investigation of the challenges associated with the successful assimilation of AI in the public sector. An implication for managers in public sector organizations who are contemplating developing AI-powered public services is the need to assess the 'organizational readiness' (Weiner, 2009) of their employees, as simply acquiring AI technology does not imply improved processes and services.

Despite the media hype surrounding the potential benefits of AI in the public sector, the study findings empirically establish the challenges and concerns of AI assimilation that key decision-makers should consider. Specifically, an implication for public sector managers and key decision makers is the need to develop and implement AI assimilation strategies that can contribute to embedding AI-powered capabilities within and throughout the organization, which in turn lead to both business and social value to be generated by the specific AI technology. Further, such strategies and the associated metrics to measure return-on-investment need to have long-term as it can take years to realise the business and social value of AI technologies (Brynjolfsson & Mitchell, 2017).

A key finding of this study is the importance of the reciprocal relationship between situated attention and structural distribution of attention as they are influential in the successful assimilation of AI in public sector organizations. Therefore, managers and key decision makers in the public sector need to consider the not only the technological aspects of AI applications but also to understand in-depth, the nuances unique to organizations within the public sector. In doing so, the benefits and changes of AI will be sustainable and tangible (Brynjolfsson & Mitchell, 2017) through improved decision-making, better policies, and superior public values such as security, safety, accountability, and transparency (Matheus, Janssen, & Maheshwari, 2020).

Table 5
Research Agenda.

Challenge	Example Research Questions
Misalignment between AI decision-making and management decision-making	• What is the technology strategy that promotes effective communication between departments? • How and when organizational need to take some action and make communication between departments better? • What is the method that makes decision-makers and technical managers on the same page? • How do decision-makers/leaders raise awareness of adopting AI and its importance in the organization? The training course, coaching, etc. • What is the strategic plan to open a dynamic channel, either internal between departments or external cross-collaboration between different related organizations? How? and when? • What kind of action do they need to tackle these challenges?
Tensions with linguistics and national culture	• How do decision-makers/ technical managers deal with the shortage of Arabic Language Processing tools? • In terms of cultural context, how do they work on compatibility, specifically in the separate gender departments? • How does an organization identify their culture and backgrounds as factors that may need machine learning and training tools (dealing with different Saudi government authorities based on their culture)? • How do these tools adapt the geo-spatial data as input to AI models?
Developing and implementing AI infrastructure	• How do leaders and decision-makers establish a well technological infrastructure to handle the enormous data efficiently? • How do managers/decision-makers' ability to changes the perception of employees about the "fear of losing their job or being replaced by AI" for them to accept and establish a solid infrastructure? • Do they run a technical partnership with other organizations to tackle this challenge instead of waste time, effort, and budget to reinvent the wheel? How do the leaders cope with these challenges in terms of efforts unity? • Is this cross-collaboration will help the organization to manage resources?
Data integrity and sharing	• How do managers and decision-makers manage and streamline the data sharing process internally and externally? • How do managers and decision-makers raise awareness of the importance of data sharing to achieve solid AI implementation? • Who is going to lead the data structure policy in terms of privacy and policy?
Ethical and governance concerns	• What is the importance of AI governance in public sector organizations? • How to set up a comprehensive and robust ethical regulation in their organization? How? Who is in charge? • How to activate these regulations under the general government law, such as self-drive cars, robots, machine learning bias? • Who oversees ethical and lawful basis circumstances of AI and Data offend, for instance, governors, leaders, AI programmer, Data engineers, users, citizens, etc.?

5.3. Limitations and future research

As with all research, however, we acknowledge this study has two limitations, which also offer directions for future research. First, the collection and analysis of the data from the cases studied is inherently bound to time and culture. Therefore, other challenges are likely to emerge as each case matures in its adoption and implementation of AI. Second, the research represents a snapshot in time of the three cases studied. Future research could adopt a longitudinal approach or apply a different theoretical lens such as organizational learning, activity theory, or design science to further advance our understanding of AI assimilation in the public the sector. Despite these limitations, the findings of this study provide a research agenda to overcome the challenges of AI assimilation in the context of public sector organizations. The research agenda contains a set of research questions emerging from the reported challenges (see Table 5), for each challenge, we set out a range of example research questions.

6. Conclusion

This study draws on attention-based view theory to study the assimilation of AI in the context of public sector organizations in Saudi Arabia. The findings demonstrate that 'situated attention' and 'structural distribution of attention' is key to embedding AI into existing processes. This study demonstrates that adopting AI requires consideration of not just its technical characteristics, but to take into consideration the context of its intended use and the readiness of the organization. In addition, the findings highlight that key decision-makers play a critical role in directing organizational attention, depending on the organizational, sector and national context, specifically when dealing with a complex technology such as AI. Concluding, public sector organizations need to continually learn how to balance the social and technical aspects of AI as both can directly and indirectly have a positive or negative impact on people internal and external to the organization.

Author statement

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Albandari Alsharani, Denis Dennehy and Matti Mantymaki. The first draft of the manuscript was written by Albandari Alsharani, and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Acknowledgements

This research was supported with the financial support that was administered by Saudi Arabian Cultural Bureau (Dublin) on behalf of Taif University, Saudi Arabia.

Appendix A. Interview Guide

Interview Phase	Interview Questions	Interviewee Notes
Settling-in (5 mins)	1. Tell me about your current role? 2. How many years are you working at current organization? 3. How many years industry experience do you have?	
Core (55 mins)	Adoption & Use of AI (20 min): 1. What application of AI do you use? (i.e., Machine Learning, Robotics, Natural	

(*continued on next page*)

(*continued*)

Interview Phase	Interview Questions	Interviewee Notes
	Language Processing, Speech Recognition, Machine Vision, or Expert Systems) 2. How does your organization use AI (i.e., process, new services)? 3. What benefits has your organization realized from AI? 4. What challenges have you encountered using AI? 5. How has AI changed the organizational structure (roles, reporting), processes, and culture? Decision Making (20 min): 1. How has AI changed the decision-making process of your organization? 2. How do you see the interplay and collaboration between humans and AI in general and with respect to decision-making in particular? 3. How does AI technologies facilitate the decision-making process? 4. What type of decision-making process did AI support or replace at your organization? 5. Do you think that AI technologies could complete a decision-making process autonomously, or is it just a tool to support and enhance this process? 6. If you plan to adopt AI or develop AI-powered services using AI? Do you usually make decisions alone or with a group? with whom? Governance (15 min): 1. What ethical issues does AI raise for public sector organizations and the wider society? 2. Does your organization have ethical guidelines for use of AI? Why? Why not? 3. How do you ensure that AI operates as it is intended to operate? 4. What kind of governance mechanisms do you have in place for AI? Why these? If no, why not?	
Wrap-up (5 mins)	We are coming to the end of the interview, and I am wondering if there are any points that you would like to add?	

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