Government Information Quarterly xxx (xxxx) xxx

Contents lists available at ScienceDirect

Government Information Quarterly

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

Harnessing the Potential of Artificial Intelligence to Foster Citizens' Satisfaction: An empirical study on India

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ARTICLE INFO

Keywords:
Artificial intelligence
AI-enabled services
Public services
Citizen satisfaction
Risk
India

ABSTRACT

Governments are increasingly employing artificial intelligence (AI) enabled services though this is still a relatively new concept that is in nascent stages of implementation. Despite growing emphasis by governments on employing AI-enabled services, many citizens are skeptical of their benefits; this makes an analysis of AI-enabled services an important area of research, especially from the perspective of citizens. This paper employs IT assimilation theory and public value theory to develop a theoretical model that examines whether the introduction of AI-enabled services would generate public value for citizens in India. The model employs the Partial Least Square-Structural Equation Modeling (PLS-SEM) technique to examine how risk factors impact the uptake of AI-enabled services in India. Based on 315 interviews conducted in India, the study highlights that the breadth and depth assimilation of AI-enabled services positively impacts and enhances the satisfaction of citizens, which in turn generates public value.

1. Introduction

Artificial intelligence (AI) describes a set of advanced general purpose digital technologies that enable machines to do highly complex tasks effectively (Hall & Pesenti, 2017). The use of AI offers immense potential for increasing productivity. It can support firms and people to use resources more efficiently by streamlining interaction between departments as a result of drawing information from large sets of data (Chatterjee, 2020a, 2020b; Chohan, Hu, Khan, Pasha, & Sheikh, 2021). Government agencies in many developed and in some developing countries have adopted AI in day-to-day operational services to provide services for citizens seamlessly (Smith & Heath, 2014). The analysis of data sets aims to support decision making by governments, address common problems and enhance the provision of public services by improving safety and security in a transparent manner (Chatterjee, Kar, Dwivedi, & Kizgin, 2019; Matheus, Janssen, & Maheshwari, 2018). AI also supports conducting data analysis accurately for better governmental performance and improved interaction with citizens, in order to offer citizens better services and thereby foster overall public satisfaction (Matheus et al., 2018). Currently, both governments and private sectors generate data in areas such as education, energy, healthcare, fraud and complaints (Anand, Medhavi, Soni, Malhotra, & Banwet, 2018; Zuiderwijk, Vhen, & Salem, 2021). Other examples of existing AI services include communicating with computers in natural language, deriving new insights from transport data, operating autonomous and adaptive robotic systems, managing supply chain, and designing more lifelike video games (Valle-Cruz, Criado, & Ruvalcaba-Gomez, 2020). In the current data-driven world, appropriate decision making guided by accurate data analysis reinforced by AI technology is important (Chatterjee et al., 2019) and considered an integral component of enhancing the predictive power of public policy systems (Chatterjee, Nguyen, Ghosh, Bhattacharjee, & Chaudhuri, 2020). To achieve effective service delivery, governments have launched initiatives to utilize the predictive power of AI for policy making (Butcher & Beridze, 2019). It is increasingly evident that the use of AI in government initiatives has become a necessity due to the rapid advancement of technology and the availability of exponential enhancement of data (Liu & Kim, 2018). In particular, AI has become more relevant following the outbreak of the COVID-19 pandemic when there has been an upsurge in the exploration and use of AI services and data analytical tools (Sipior, 2020).

Prior to the pandemic, several governments were employing AI for diverse functions that ranged from managing welfare schemes and

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https://doi.org/10.1016/j.giq.2021.101621
Received 23 December 2020; Received in revised form 24 July 2021; Accepted 25 July 2021

healthcare to tackling crime. For example, AI is used to identify claim patterns for government welfare programs, and AI-powered fraud detection techniques are used to tackle false claims and address corruption at individual and institutional levels. Machine learning algorithms are also used to identify patients with similar symptoms in different locations to control the spread of diseases. In addition, AI services support governments with policing heat maps to predict when and where crimes are likely to happen. However, as with other technologies, studies document that AI adoption by both the Indian government and the private sector faces significant barriers before any public value can be realized (Liang & Qi, 2017; Mohammed, Alzahrani, Alfarraj, & Ibrahim, 2018). While technology adoption is considered a component of the initial stage, the success of AI adoption is realized only after wide-scale assimilation (Wang et al., 2016; Wei, Lowry, & Seedorf, 2015). Technology assimilation is considered a complete life cycle that spans breadth and depth assimilation of AI-enabled services, and which includes evolution, adoption, and complete deployment of innovation (Zhu, Kraemer, & Xu, 2006). Breadth assimilation (horizontal) is associated with the diversity and scope of AI technology usage whereas depth assimilation (vertical) is related to the intensity of AI technology usage, i.e. how AI technology is being used by governments (Gallivan, 2001; Zhang, Xue, & Dhaliwal, 2016). The assimilation gap is attributed to the fact that actual use often lags behind the decision to adopt AI in government sectors (Chatfield & Reddick, 2018). Further, since AI substitutes for humans, the application of AI services is associated with risks (Butterworth, 2018; Čerka, Grigienė, & Sirbikytė, 2017), which can impact decision-making processes and, in some instances, have a detrimental effect on implementation of AI services. Major implementation issues include principles of explicability, beneficence, nonmaleficence, and justice, together with privacy and security (Floridi et al., 2018).

Extant literature discusses the applications of AI and associated technological aspects. Few studies, however, examine the impact and challenges of AI applications faced by government sectors (Liu & Kim, 2018; Sharma, Yadav, & Chopra, 2020). This paper investigates how successful AI applications are likely to support accurate decision making and can provide high-quality public services to the citizens. The following research questions are examined:

RQ1. How can the use of AI-enabled services by different government departments foster the satisfaction of citizens?

RQ2. Can the depth assimilation and breadth assimilation of AI-enabled government services impact the operational and strategic public services being delivered to citizens?

RQ3. Is there any moderating impact of risk factors that may influence the quality of AI-enabled services and public values?

The paper is structured as follows. Section 2 discusses existing literature and related theories. Section 3 explores different hypotheses that enable us to develop the conceptual model. Section 4 discusses the research methodology and validates the conceptual model with the sample data. Section 5 discusses the main findings. Section 6 presents theoretical contributions followed by practical implications, the main limitations and the direction for future research, followed by conclusions in Section 7.

2. Literature review

The use of data analytics has played an important role in decision making by governments to improve public values (Matheus et al., 2018; Valle-Cruz et al., 2020). The analysis of data helps government sectors to adopt appropriate decisions that, in the long run, foster citizens' satisfaction (Dwivedi, Weerakkody, & Janssen, 2012). Data analysis can be conducted without human assistance in a cost-effective manner and employed accurately and efficiently with AI technology (Chatterjee, Ghosh, Chaudhuri, & Chaudhuri, 2020). Different government bodies are exploiting the full potential of data for accurate decision making to solve the problems of its citizens (Butcher & Beridze, 2019; Chohan et al., 2021). AI adoption is supporting governments to achieve higher integration of operational procedures, which is expected to considerably improve the overall strategy of governmental policies (Alonso, Escalante, & Orue-Echevarria, 2016; Chatterjee, Kar, & Gupta, 2018; Leuprecht, Skillicorn, & Tait, 2016; Sharma, Al-Badi, Rana, & AL-Azizi, L., 2018; Zuiderwijk et al., 2021). Despite the benefits, several government agencies face impediments to AI technology deployment and development, and operation of e-government systems (Chatterjee, 2020a, 2020b; Liang & Qi, 2017; Mohammed et al., 2018). The presence of barriers has translated into a lack of full-scale assimilation of AI-enabled services by all government sectors (Lowry, Wei, & Seedorf, 2015; Wang et al., 2016). The complete assimilation of an innovation has salient stages which include evolution, adoption and deployment (Zhu et al., 2006). While innovation 'becomes an integral part of value chain activities' (Wei et al., 2015, p. 629) the innovation process includes initiation and utilization of a program, product and practice in an organization (Rogers, 2010). The adoption of AI technology by an organization is considered a stage-based process which ranges from pre-adoption (initiation), then decision for adoption, to post-adoption (Hameed, Counsell, & Swift, 2012).

In terms of IT assimilation theory, for any AI implementation issue an assimilation gap exists (Rai, Brown, & Tang, 2009). The contribution of any innovation cannot be capitalized until it is fully assimilated by addressing the gap (Liang, Saraf, Hu, & Xue, 2007). In the context of IT-related assimilation dimensions (Klein, 2012), the depth and the breadth of usage of AI technology are considered building blocks for AI assimilation (Zhang et al., 2016). The assimilation depth of AI is associated with the concept of vertical impact of AI technology usage in governmental initiatives, whereas the breadth of AI assimilation refers to the opportunity of government agencies to use AI technology (Zhang et al., 2016). The effective use of AI technology helps to analyze data for accurate decision making, that in turn enhances public value by delivering effective public service to citizens. The IT-related public value is divided into two categories: operational and strategic public service for citizens (Cordella & Bonina, 2012). The operational public service for citizens reflects the improvement of efficiency towards IT-related technology operation, whereas the strategic public service for citizens refers to the achievement of strategic social goals associated with transformational issues that provide complete satisfaction (Cordella & Bonina, 2012). AI applications invite some security and privacy issues, as they can analyze various types of data including personal data (Chatterjee et al., 2019). This risk factor might create a hindrance to providing an effective service to citizens, and for this reason governmental agencies need to reconcile the situation (Sharma et al., 2018). Literature highlights the use of AI in the government sector (de Sousa, de Melo, Bermejo, Farias, & Gomes, 2019) with a focus on the technological aspects of AI applications (Liu & Kim, 2018). However, AI usage in government administration models associated with governance implications has remained largely underexplored (Sharma et al., 2020). Dwivedi et al. (2012) investigated the maturity model in government sectors and the challenges to successfully implementing different e-governance applications in government sectors. But this study did not investigate the depth and breadth assimilation of different e-governance applications in government sectors. Alonso et al. (2016) explained the transformational cloud government (TCG) process for the transformation of public administration, but this study did not discuss operational and strategic public services to citizens by government. Leuprecht et al. (2016) and Mohammed et al. (2018) investigated cyber risks and security-related models for cloud computing fitness for e-government implementation. Both these studies described the decision-making implementation process for e-government, but they did not explore the decision-making process with the help of AI in public administration. Liang and Qi (2017), Matheus et al. (2018) and Sharma et al. (2018) investigated the effectiveness of e-governance mechanisms for better decision making, predictive modeling and accountability for decision making in government sectors. But these studies did not explore the breadth and depth assimilation of AI-enabled services in government sectors, or investigate citizen satisfaction. Butcher and Beridze (2019), Valle-Cruz et al. (2020) and Chatterjee (2020a, 2020b) analyzed the usage of AI in different government sectors and related policies on decision-making criteria by the application of AI in public administration. However, none of these studies ventured to investigate the prospect of decision making by AI for operational as well as strategic public services for deriving benefits to citizens. Sharma et al. (2020), Zuiderwijk et al. (2021) and Chohan et al. (2021) described different AI-related governance mechanisms to be applied in public governance. These studies also investigated the design and behavioral science in government-to-citizens cognitive communication strategy and the related decision-making process. But none of these studies investigated the depth and breadth assimilation of AI-enabled services by governments to citizens, nor did they explore the operational and strategic decision-making process by governments for better public administration.

From the above discussions, it is seen that none of these studies explored the breadth and depth assimilation of AI-enabled services to citizens by governments. None of these studies explained the operational and strategic decision-making process with the help of technologies by governments. Finally, these studies did not explore the issue of citizen satisfaction due to accurate and faster decision-making processes by governments with the help of new technologies including AI. In such a scenario, the present study has attempted to investigate the above-mentioned unexplored areas. The summary of literature on government decision-making processes using AI and other technologies is provided in Table 1.

Table 1
Summary of literature on government decision making.

Source	Area of research	Key findings
Dwivedi et al. (2012)	This study investigated the maturity model in government sectors. It also described the growing sophistication of and challenges in implementation of e-governance applications and the decision-making process.	- Maturity model for e-governance - Challenges to successful implementation of applications
Alonso et al. (2016)	This study explained the transformational cloud government (TCG) process for transforming public administrations.	- Cloud computing applications for public services
Leuprecht et al. (2016)	This study investigated cyber risks, cyber security and related models.	- Advancement of castle model for cyber security
Liang, Qi, Wei, and Chen (2017)	This study investigated the effective e-governance mechanisms for cloud computing adoption in China. It conducted and analyzed multiple case studies.	- Determined the key antecedents for cloud computing adoption - Effective e-governance adoption in China
Mohammed et al. (2018)	This study investigated cloud computing fitness for e-government implementation. This study also conducted the performance analysis for better decision making and implementation.	- Fitness mechanisms for cloud computing in e-governance implementation
Matheus et al. (2018)	This study explored the opportunity of data science for decision making and empowering the public especially focusing on smart cities.	- Data-driven dashboard - Accountability for decision making
Sharma et al. (2018)	This study described different opportunities for mobile applications in government services. It also showed a predictive modeling for such mobile applications in government sectors.	- Mobile applications for government sectors for decision-making process
Butcher and Beridze (2019)	This study investigated the state of artificial intelligence governance internationally.	- Global status of AI applications for government projects
Valle-Cruz et al. (2020)	This research study assessed the public policy cycle framework for the application of AI. It also discussed policy evaluation.	- AI-related policy and decision-making process - Policy cycle framework helping decision making
Chatterjee (2020a, 2020b)	This study investigated the Indian government AI strategy and its challenges. It also described various challenges of AI adoption and its decision-making process.	- India-centric AI strategy - Decision making using AI - Adoption challenges for AI applications in India
Sharma et al. (2020)	This paper described different AI-related governance mechanisms. It also provided a comprehensive review and critique, and proposed areas for future research scope.	- AI and effective governance - Research agenda for the future
Zuiderwijk et al. (2021)	This paper described different implications of the use of AI in public governance. It conducted a systematic literature review and proposed a research agenda for future researchers.	- Implications of AI for public governance - AI applications and decision science for effective public governance
Chohan et al. (2021)	This research investigated the design and behavioral science in government-to-citizens cognitive-communication strategy with decision-making process.	- Developed a framework for government-to-citizen cognitive communication

3. Theoretical background, conceptual model and hypotheses development

3.1. Theoretical background

The IT industry and academics have recognized the overall impact of IT-related performance at the organizational level (Klein, 2012; Rai et al., 2009). The breadth and depth assimilation of AI technology, taken from the concept of IT assimilation theory (Liang et al., 2007), is perceived to have different impacts on different government departments (Fang, Palmatier, & Grewal, 2011). The IT assimilation theory posits that an organization needs to use simultaneously breadth and depth assimilation of suitable technology for better operational performance (Balasubramanian, Al-Ahbabi, & Sreejith, 2019). This theory also highlights that the use of breadth and depth assimilation creates better operational and strategic performance (Lyytinen & Damsgaard, 2001; Zhang et al., 2016). In terms of IT assimilation theory, it is interpreted that the adoption of any technology is in the initial stage of the assimilation cycle (Klein, 2012). The cycle includes evaluation, adoption and, eventually, deployment of the technology to create public value for improving operational as well as strategic public services for citizens (Armstrong & Sambamurthy, 1999). Thus, the theory assists in interpreting how AI applications employed by different government departments could ease processes to support citizens. If the algorithms are biased or the automated systems malfunction, or if, due to unavailability of trained manpower in the government departments AI-enabled applications are not maintained and upgraded, the operational and strategic public services are likely to be adversely impacted. This may invite several risks, such as an infringement of the personal data of citizens that could jeopardize their privacy and pose a security threat. This may undermine the credibility of governmental services using AI technologies and adversely affect the participation of citizens in those services.

The public value theory (Moore, 1995) plays a significant role in operational and strategic public services (Fisher & Grant, 2012; Roman & McWeeney, 2017). This theory reformulates government administration to function independently for enhancing effective services for citizens' best satisfaction; it provides inputs to government agencies on how different policies could be implemented to minimize expenditure and maximize services for citizens' satisfaction (Bryson, Crosby, & Bloomberg, 2014; Van der Waal, Tina, Nabatchi, & Graaf, 2015). To achieve the goal of citizens' satisfaction, governmental agencies are required to operationalize and strategize public services to improve public value, which is the main theme of public value theory (Dahl & Soss, 2014). In this manner, the public value theory helps to examine how the assimilation of technology in public services is likely to benefit citizens (John & Moore, 2011).

3.2. Proposed conceptual model

A combination of IT assimilation theory and public value theory explains how the effective use of AI technology by government agencies is likely to provide public services that ensure citizens' satisfaction. Several adoption-related theories, such as TAM (Davis, 1989), UTAUT (Venkatesh, Morris, Davis, & Davis, 2003) and the Information Systems (IS) Success model (DeLone & McLean, 1992) can explain the rationale for the adoption of AI-enabled services in different government departments. But these neither delve into the breadth and depth assimilation of AI services nor explain the issue of benefits for the public. This paper, therefore, uses IT assimilation theory to explain 'assimilation depth of AI-enabled services' and 'assimilation breadth of AI-enabled services', which are the constructs of this study. From the public value theory, we borrow 'operational public service to citizens' and 'strategic public service to citizens' as two additional constructs which are likely to impact 'citizen satisfaction' towards using AI-enabled government services to citizens. Fig. 1 presents the conceptual model by drawing on extant literature to highlight the relationship between the theory and results and the hypotheses developed.

3.3. Hypotheses development

Based on the review of literature and within the overall framework of the IT assimilation and public value theory, we examine the impact of two factors (depth assimilation and breadth assimilation) on public value, categorized as operational and strategic public services that impact citizens' satisfaction level in line with Twizeyimana and Andersson (2019). The relationship between the assimilation of AI-enabled services and public value is likely to be influenced by several risk factors. These include privacy and security issues that may arise from an uncontrolled use of citizens' personal data. We explain these variables and formulate the hypotheses to develop a conceptual model.

3.3.1. Assimilation dimensions (depth and breadth) of AI-enabled services

Government sectors improve operational performance by employing and assimilating IT. For example, the assimilation of internet-based purchase applications impacts on operational performance (Klein, 2012). Sallehudin, Razak, and Ismail (2016) indicate that the deployment of technology significantly impacts the operational effectiveness of organizations, and that the application of AI technology helps government agencies to analyze voluminous data accurately, quickly and cost effectively (Chatterjee et al., 2019). The usage of IT applications in any organization is associated with a process going from top to bottom (vertical shift), and from one point to another point (horizontal shift) (Klein, 2012; Liang, Qi, Zhang, & Li, 2019). Initially, this process signifies only the idea of AI applications in the government sector that is escalated slowly and steadily to other complex services to support decision management using the acquired data (Niehaves, Plattfaut, & Becker, 2013). The enhancement of depth assimilation in AI technology usage is perceived to support the core administrative and decision-making abilities of government (Sallehudin et al., 2016). Depth assimilation influences core operational processes of government (Lavie, Stettner, & Tushman, 2010). Accordingly, it is hypothesized as follows:

H1. *: Assimilation depth of AI-enabled services (ADES) positively affects operational public service for citizens (OPSC).*

Assimilation in an organization is considered a critical step in the context of realization of a system for delivering benefits to the organization. Employees of the organization transform the system capability to derive organizational performance through their daily activities (Klein, 2012). The assimilation process is categorized in two groups: breadth assimilation and depth assimilation. Breadth assimilation is concerned with the number of users together with the percentage of the corresponding business processes which are involved in the use of the technology (Floridi et al., 2018). In the context of functions of government through breadth assimilation, the scope of the government agency determines whether or not to use a system or a technology like AI. Breadth assimilation is reflected in the adoption of a system, the quantity of services involved in the system adopted by the government agency, and the quantity of the system which has been migrated to different departments of that government agency (Zhang et al., 2016). Enhancement of breadth assimilation impacts AI deployment efficiently. The digitalization process adopted by other agencies is extracted to the government agencies in this digitalized environment and this impacts the operational procedure of the government departments. Accordingly, it is hypothesized as follows:

H2. *: Assimilation breadth of AI-enabled services (ABES) positively affects operational public service for citizens (OPSC).*

The depth assimilation of AI technology is perceived to provide considerable benefits to citizens when it is adopted by government agencies. The depth assimilation of AI technology will help to automate the processes and practices of different government departments, enhancing the overall performance of government agencies to provide

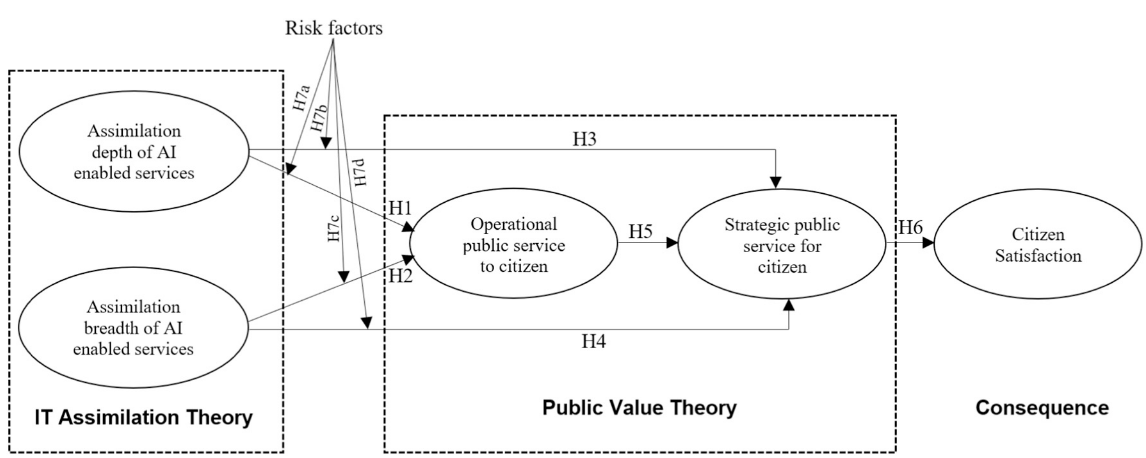

Fig. 1. Proposed conceptual model (Sources: Moore, 1995; Liang et al., 2007).

benefits to citizens. The improvement of the overall performance of the government agency is perceived to influence its strategic performance management (Balasubramanian et al., 2019). Strategic performance management is conceptualized as a concerted approach to help an organization to achieve its goal. In terms of the assimilation theory, government agencies involved in the depth assimilation for AI technology need to evaluate, adopt and eventually deploy AI technology in the different functionalities of the government department in order to bring about better strategic performance (Lyytinen & Damsgaard, 2001; Zhang et al., 2016). Thus, when by depth assimilation the different departments of a government agency are able to deploy AI technology intensively, the strategic public service to the users is perceived to be improved. Accordingly, it is hypothesized as follows:

H3. *: Assimilation depth of AI-enabled services (ADES) positively and significantly impacts strategic public service for citizens (SPSC).*

The assimilation breadth of AI-enabled services by government agencies is perceived to provide benefits to citizens making use of such services. Breadth assimilation in the context of AI technology refers to the extent of available scope for the government agency to use and adopt AI (Zhang et al., 2016). It shows the diversity and the number of systems using AI platforms. Breadth assimilation regarding AI-assimilation signifies how many types of AI applications have been used by a government agency and the quantity of this system migrated by the government agency (Liang et al., 2019). Breadth assimilation helps to extend the usage of AI technology by the government agency with coverage of informatization (Liang et al., 2007). Breadth assimilation of AI technology is perceived to impact the strategic performance of government agencies. Complete assimilation of AI technology in government sectors is perceived to drive government agencies towards better strategic performance. Accordingly, it is hypothesized as follows:

H4. *: Assimilation breadth of AI-enabled services (ABES) positively and significantly impacts strategic public service for citizens (SPSC).*

Several studies highlight that strategic and operational values can be derived by IT usage in any organization (Hitt & Brynjolfsson, 1996; Liang et al., 2019). Others recommend that, for achieving strategic competitive performance, operational improvement acts as an effective intermediate dependent variable (Zhang et al., 2016) which establishes a sequential connection between operational and strategic performance (Dong, Xu, & Zhu, 2009). In business literature, it is the overall performance that improves the strategic performance, but this requires a long-term commitment (Alford & O'Flynn, 2009). In the context of government administration, IT values to support public services are developed over time (Bannister, 2001). The provision of strategic public services is a complex process compared to operational services, and the former is the result of the ability of government agencies to create conducive environments (Li, Du, Xin, & Zhang, 2017). Thus, operational public service for the benefit of citizens is perceived to impact the strategic public service provided to the beneficiaries in the context of use of AI by government agencies. Accordingly, it is hypothesized as follows:

H5. *: Operational public service for citizens (OPSC) positively influences strategic public service for citizens (SPSC).*

3.3.2. Effects of providing strategic public service to citizens: Impact on citizen satisfaction

Strategic public service for citizens refers to the delivery of quality public service, at lower information cost, that provides accessibility to public services, fosters citizens' participation in government and narrows the digital divide (Akman, Yazici, Mishra, & Arifoglu, 2005; Jaeger & Thompson, 2003). The provision of strategic public service to citizens provides an effective framework to examine the performance of the administration in creating public value for citizens (Alford & O'Flynn, 2009). Heeks (2008) proposes a set of indicators to measure the delivery of public value which includes the level of user satisfaction. Effective delivery of strategic public service for citizens depends also on how satisfied citizens are. This is reflected in an individual's experience of using the public service delivered by government agencies (Horan & Abhichandani, 2006; Kearns, 2004). These discussions help to formulate the following hypothesis:

H6. *: Provision of strategic public service for citizens (SPSC) significantly and positively impacts citizen satisfaction (CS).*

3.3.3. Moderating effect of risk factors

AI technology helps governments to analyze data accurately to improve the decision management architecture (Niehaves et al., 2013). Since AI technology primarily supports data analysis of a diverse nature without human assistance, there is potential to use personal data that can jeopardize the security and privacy concerns of the data subject (Chatterjee & Sreenivasulu, 2019). This affects the AI assimilation process regardless of whether the assimilation is vertical or not, and impacts government agencies' performance (Liang et al., 2019). AI assimilation by government agencies helps citizens to access several government services seamlessly (Smith & Heath, 2014). Government agencies need to analyze different data sets by AI so as to help the government to address citizens' concerns. AI applications in the government sector are expected to solve the different issues that occur. In the process of AI assimilation by the government sector, several dimensions of assimilation provide the basis for measuring the extent of use of AI, amongst which depth assimilation deserves special mention (Massetti & Zmud, 1996). Depth assimilation in terms of AI usage is associated with the intensity with which government agencies deploy AI towards aligning different government functions. This indicates the vertical impact of the deployment of AI on governmental administrative activities (Zhang et al., 2016). Government with depth AI assimilation may integrate some specific processes (Klein, 2012). This is perceived to have impacted on the operational efficiency of public services. However, analysis of several public data sets by AI in order to provide better public services invites the risk of breaching the privacy of personal data. Accordingly, it is hypothesized as follows:

H7a. *: Risk factors act as a moderator to impact the relationship between the assimilation depth of AI-enabled services (ADES) and operational public service for citizens (OPSC).*

It is known that data analytics plays a critical role in the context of evidence-based decision making in the public sector (Matheus et al., 2018). The public and private sectors generate a large amount of data covering several areas. Recently, the public sector has given greater emphasis to analyzing this huge volume of public data in order to extract their full potential in decision making. It has become an effective enabler for ensuring better government performance and would help governments to adopt better strategy. To this end, governments are trying to harness the power of AI to analyze these data (Butcher & Beridze, 2019). But the use of AI in the analysis of personal data, for the improvement of government administration and to serve citizens better, invites privacy risks. Government is trying to use the full potential of AI through depth assimilation (Zhang et al., 2016) by analyzing different kinds of data. Depth of AI assimilation is perceived to impact public service strategy for citizens. But if appropriate precautions are not taken, there is the risk of misusing citizens' personal data at the cost of their privacy (Chatterjee et al., 2019). In such a situation, it is perceived that these factors might act to influence the relationship between depth of AI assimilation and the strategic performance of government agencies. Accordingly, it is hypothesized as follows:

H7b. *: Risk factors act as a moderator to impact the relationship between the assimilation depth of AI-enabled services (ADES) and strategic public service for citizens (SPSC).*

The decision management process must be robust and accurate in the government sector (Zhang et al., 2016). This is facilitated by the application of AI (Niehavers et al., 2013) which enables analyzing diverse data, including personal information, thereby inviting the risk of infringement of the personal data and jeopardizing the citizens' privacy (Chatterjee & Sreenivasulu, 2019). Nonetheless, with the help of AI, government can solve many of citizens' common issues without any flaw. Several measurement dimensions are used to measure the extent to which AI can help government (Massetti & Zmud, 1996). Amongst these dimensions, breadth assimilation plays a critical role (Liang et al., 2019). Breadth assimilation is considered a building block for AI assimilation in the government sector and for its deployment. Specifically, the breadth of AI assimilation is conceptualized as the scope of government towards the extent of coverage of AI assimilation in different government departments. It is concerned with the types of AI technology used, the quantity adopted, and the quantity of the system migrated to others (Zhang et al., 2016). It is a fact that breadth assimilation of AI technology by government is perceived to improve the operational process, but the impact of risk factors cannot be ignored as discussed earlier. Accordingly, it is hypothesized as follows:

H7c. *: Risk factors act as a moderator to impact the relationship between the assimilation breadth of AI-enabled services (ABES) and operational public service for citizens (OPSC).*

The generation and processing of data in the current age of data deluge has taken a new shape due to the arrival of new technologies such as big data analytics, machine learning and AI. Moreover, the arrival of AI has brought a new ramification to the data analysis landscape. In this favorable environment, government agencies are coming forward to assimilate AI in order to develop the public administrative system (Matheus et al., 2018) and to serve citizens better. There is a growing interest in the government sector to use AI in data analysis for accurate decision making (de Sousa et al., 2019). The Indian government is trying to analyze the collected data of citizens in different ways. One of the ways to assimilate these data is breadth assimilation (Zhang et al., 2016). This process highlights the extent to which the government can deploy its AI-enabled applications in different governmental departments. But whatever process is employed for assimilating data to develop public sector strategy, the apprehension of breaching the security of public data will exist and hence there is a risk (Ku & Leroy, 2014). Risk factors are deemed to have influenced the relationship between 'assimilation breadth of AI-enabled services' and 'strategic public service for citizens'. Accordingly, it is hypothesized as follows:

H7d. *: Risk factors act as a moderator to impact the relationship between the assimilation breadth of AI-enabled services (ABES) and strategic public service for citizens (SPSC).*

4. Research methodology

To validate the model, a survey questionnaire was developed and administered to government agencies in India that have adopted different services which use AI technology. The items (instruments) were drawn from literature and from the inputs of the constructs. The items on the depth and breadth of AI service assimilation were adopted from existing literature (Klein, 2012; Sallehudin et al., 2016). Four items for each construct (depth and breadth) were prepared. The items covering operational and strategic public service for citizens were adopted from Dong et al. (2009) and Li et al. (2017). To prepare the five items relating to citizen satisfaction, inputs from Horan and Abhichandani (2006) were used. For the proposed model, 21 questions were prepared. Details are provided in Appendix A. Since most government agencies in India use the English language, the questions were in English. All items were measured on a 5-point Likert scale ranging from 1 = Strongly Disagree (SD) to 5 = Strongly Agree (SA). Appropriate fine tuning of the questions was undertaken based on the comments of six experts in the pre-pilot phase. This phase was administered on 15 government agencies with the aim of reviewing the questionnaire and ensuring it was comprehensive and well designed. These 15 government agencies have not been considered in the main survey.

We contacted the Ministry of Electronics and Information Technology, the National Informatics Center (NIC) and the Unique Identification Authority of India (UIDAI), Government of India, amongst other government agencies. To enhance the validity of the content, we adopted the 'Key in format' approach (Martins, Oliveira, & Thomas, 2016). We identified respondents who were involved in AI-related projects and possessed a basic knowledge of AI-related technology. With this approach, we identified 491 prospective respondents. A set of 21 questions was given to all the potential respondents with a request to complete the survey in two months (January to February 2020). The respondents were contacted in the intermediate period to ensure their replies would be received by the deadline. Within the scheduled time we received 331 replies. We scrutinized all the responses, of which 16 were incomplete and therefore excluded from the analysis. In these 16 responses, some respondents put tick marks against more than one option for each question while others left the response sheet completely empty. Hence, we considered 315 usable replies with 21 questions for the analysis. The demographic information of 315 respondents is in Table 2.

This study used the Partial Least Square (PLS)-Structural Equation Modeling (SEM) technique to test the hypotheses. The PLS-SEM technique involves quantification of the responses received in the survey. Studies recommend SmartPLS 3 software to empirically assess the conceptual model (Hair, Risher, Sarstedt, & Ringle, 2019; Hair, Sarstedt, Ringle, & Gudergan, 2017). The PLS-SEM technique is a variance-oriented technique that has several advantages for analyzing data, especially for data that are not normally distributed, and is used for e-government studies (Pee & Kankanhalli, 2016). Further, this technique does not impose any sample restriction and yields better results in exploratory research as in the current context (Ringle, Sarstedt, & Straub, 2012; Willaby, Costa, Burns, McCann, & Roberts, 2015).

5. Results

5.1. Measurement model and discriminant validity test

For measuring the content validity, the loading factor (LF) of each instrument was assessed. To verify internal consistency, reliability, convergent validity and defects of multicollinearity, Cronbach's alpha (α), Composite Reliability (CR), Average Variance Extracted (AVE) and Variance Inflation Factor (VIF) of each construct are estimated. The estimated values of all the different parameters are within allowable range, and the results are presented in Table 3.

Following Fornell and Larcker (1981), discriminant validity is supported by the square foot of each AVE greater than the corresponding bifactor correlation coefficients. The results are shown in Table 4. The loading factors of all the items are greater than the corresponding cross loading factors confirming discriminant validity. The results are shown in Appendix B.

Table 2
Demographic information ($N = 315$).

Demographic	Particulars	Frequency	Percentage (%)
Level of government agencies	Government of India	241	76.5
	State governments	74	23.5
AI-dedicated center of excellence	Yes	46	14.6
	No	257	81.6
	N/A	12	3.8
AI-think tank establishment	Yes	72	22.8
	No	216	68.6
	N/A	27	8.6
Experience of the employees	<10 years	90	28.6
	10–20 years	199	63.2
	>20 years	26	8.2

Table 3
Results of different parameters.

Constructs/ Items	LF	AVE	CR	α	VIF	t-value	No. of Items
ADES		0.87	0.89	0.92	4.7		4
ADES1	0.96					24.26	
ADES2	0.92					28.32	
ADES3	0.90					31.87	
ADES4	0.95					26.11	
ABES		0.78	0.81	0.86	3.9		4
ABES1	0.87					17.91	
ABES2	0.94					22.92	
ABES3	0.85					26.01	
ABES4	0.87					27.47	
OPSC		0.86	0.88	0.91	3.7		4
OPSC1	0.95					20.11	
OPSC2	0.89					25.27	
OPSC3	0.94					31.39	
OPSC4	0.92					19.02	
SPSC		0.88	0.91	0.94	4.1		4
SPSC1	0.95					26.57	
SPSC2	0.95					32.48	
SPSC3	0.96					21.07	
SPSC4	0.90					34.02	
CS		0.83	0.85	0.88	4.4		5
CS1	0.85					37.88	
CS2	0.96					31.06	
CS3	0.87					18.81	
CS4	0.92					22.47	
CS5	0.85					19.07	

Table 4
Discriminant validity test.

Construct	ADES	ABES	OPSC	SPSC	CS	AVE
ADES	0.93					0.87
ABES	0.17***	0.88				0.78
OPSC	0.26	0.15**	0.93			0.86
SPSC	0.19	0.29	0.27	0.94		0.88
CS	0.29*	0.26	0.19**	0.32	0.91	0.83

Note: $p < 0.05$(*); $p < 0.01$(**); $p < 0.001$(***).

A Heterotrait–Monotrait (HTMT) correlation ratio test has been conducted to verify the discriminant validity. Results show that the values of all the constructs are less than 0.85 (Henseler, Ringle, & Sarstedt, 2014; Voorhees, Brady, Calantone, & Ramirez, 2016), which confirms the discriminant validity of the constructs. The results are shown in Appendix C.

5.2. Common method variance (CMV)

We have undertaken this study using self-reported data, and it is essential to investigate whether the collected data suffers from any bias. The Harman one-factor test is performed to determine CMV, and the first factor emerged as 33.62%, which is less than the highest cutoff value of 50% as recommended by Podsakoff, MacKenzie, Lee, and Podsakoff (2003). This confirms no distortion of results.

5.3. Moderator analysis (multi group analysis)

We also considered risk factors as a moderator that could impact the relationship between assimilation and public value. The different kinds of risks include data privacy and security-related risks, data governance risks, implementational risks, inappropriate decision-making risks and citizens relationship management-related risks (Chatterjee, 2020a, 2020b; Chatterjee & Sreenivasulu, 2019; Sharma et al., 2018). The risk factors were categorized into high and low risk. To assess the effects of the moderator on the four linkages H1, H2, H3 and H4, a Multi Group Analysis (MGA) was undertaken. For this, we considered bootstrapping procedure with 5000 resamples. This enabled computing the *p*-value differences by considering the effects of the two categories of moderator (high and low) on the four linkages. If the p-value differences become less than 0.05 or greater than 0.95, the effects of the moderator are significant on the concerned linkage (Hair et al., 2018; Hair Jr., Hult, Ringle, & Sarstedt, 2016). The multi-group analysis results are shown in Table 5.

5.4. Structural model

Structural model analysis is used to test the hypotheses (Hair, Sarstedt, Ringle, & Mena, 2012). By bootstrapping procedure (with SmartPLS 3 software) considering 5000 iterations of subsamples, the path coefficients and the levels of significance were computed to ensure the stability of results. To estimate the cross-validated redundancy, bootstrapping procedure that considers 5000 examples has been performed in line with Henseler et al. (2014). The omission separation 5 has been considered. We have estimated the Stone Geisser Q^2 value (Geisser, 1975; Stone, 1974) and its value was 0.63. The results show that the data has appropriate predictive relevance. To detect if the model is in order or not, we considered Standardized of Mean Square Root Residual (SRMR) as a standard index and the values were 0.062 for PLS and 0.030 for PLSc. Both these estimates are less than 0.08 (Hu & Bentler, 1998), and hence the results show that the model is in order. The results are shown in Fig. 2 (Structural Model) with subsamples created by random observations from the original data sets.

The results highlight that ADES and ABES have a significant and positive effect on OPSC since the path coefficients are 0.46 and 0.38, respectively, with significance level at $p < 0.001$(***). The hypotheses H1 and H2 are thus supported. The results also show that ADES and ABES have a significant and positive effect on SPSC since the concerned path coefficients are 0.16 with the level of significance $p < 0.05$(*) and 0.14 as level of significance for $p < 0.01$(**). It supports hypotheses H3 and H4. The path coefficients from OPSC to SPSC are found to be statistically significant as the concerned path coefficient is 0.30 with level of significance $p < 0.01$(**). Further, it appears from SEM analysis that the impacts of SPSC on CS are significant as the concerned path coefficient is 0.51 with level of significance $p < 0.001$(***). The effects of the moderator risk factor on the linkages are significant (Fig. 2) for the relationships that cover H1, H2, H3 and H4. In terms of the verification of the coefficients of determinants (R^2 values), which are used as descriptive measures, it appears that ADES and ABES could explain 42.8% of variation in OPSC, whereas ADES and ABES explain 56.2% of variation in SPSC. The results also highlight that SPSC could explain CS to the value of 72.7%, which is the predictive power of the model. The results are shown in Table 6.

6. Discussion

The analysis highlights that depth and breadth assimilation of AI-enabled services in governmental agencies impacts both operational (H1 and H2) and strategic performance of public services for citizens (H3 and H4). The results are consistent with previous studies on resource configuration (Fang et al., 2011; Lyytinen & Damsgaard, 2011) and supported by IT assimilation and public value theory, which emphasize significant synergy in terms of IT strategies usage to enhance the overall performance of government agencies for higher citizen

Table 5
Multi Group Analysis (MGA).

Linkages	Moderator	p-value differences	Remarks
(ADES → OPSC) × RF	Risk Factor (RF)	0.03	Significant
(ABES → OPSC) × RF	Risk Factor (RF)	0.01	Significant
(ADES → SPSC) × RF	Risk Factor (RF)	0.01	Significant
(ABES → SPSC) × RF	Risk Factor (RF)	0.02	Significant

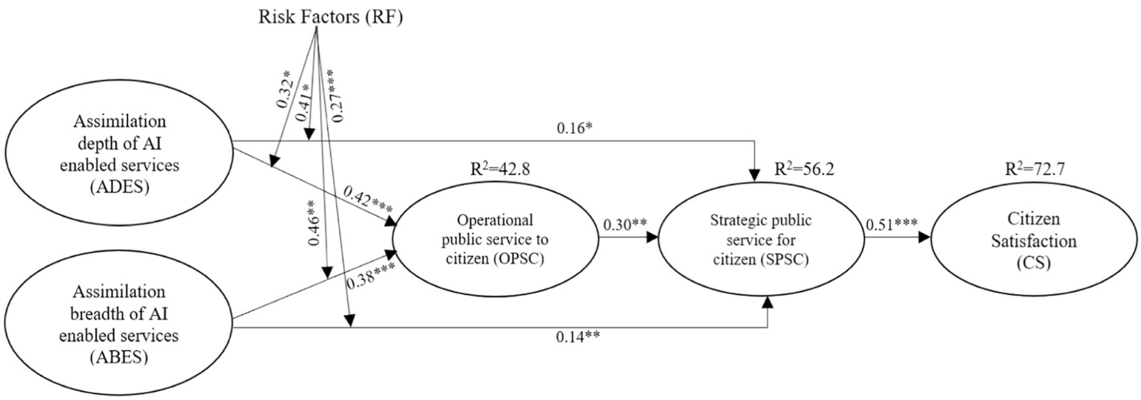

Fig. 2. Structural model.
Note: $p < 0.05$ (*); $p < 0.01$(**); $p < 0.001$(***).

Table 6
Path coefficients, *p*-values and remarks.

Paths	Hypotheses	Path coefficients	p-values	Remarks
ADES → OPSC	H1	0.42	P < 0.001 (***)	Supported
ABES → OPSC	H2	0.38	P < 0.001 (***)	Supported
ADES → SPSC	H3	0.16	P < 0.05(*)	Supported
ABES → SPSC	H4	0.14	P < 0.01(**)	Supported
OPSC → SPSC	H5	0.30	P < 0.01(**)	Supported
SPSC → CS	H6	0.51	P < 0.001 (***)	Supported
(ADES → OPSC) × RF	H7a	0.32	P < 0.05(*)	Supported
(ADES → SPSC) × RF	H7b	0.41	P < 0.05(*)	Supported
(ABES → OPSC) × RF	H7c	0.46	P < 0.01(**)	Supported
(ABES → SPSC) × RF	H7d	0.27	P < 0.001 (***)	Supported

satisfaction (Tanriverdi, 2006).

The results also find that operational public service for citizens (OPSC) significantly and positively impacts strategic public service for citizens (SPSC) (H5), which leads to higher citizen satisfaction (H6). This finding is in line with previous studies (Dong et al., 2009; Zhang et al., 2016), which confirm the view that an operational service is considered as an antecedent variable of a strategic service in the context of public policy and value. The hypothesis (H5) reflects that long-term commitment to operational service and ensuring effective and stable improvement in government administration functioning improves strategic public value for citizens through higher satisfaction levels. This is reflected in higher capability of governmental agencies (Li et al., 2017). Our study also highlights those governmental agencies must utilize the potential of AI to analyze different types of data for public value creation and higher satisfaction of citizens. However, such data analysis must address citizens' security and privacy issues (Chatterjee et al., 2019), suggesting that governmental agencies should focus on data privacy and security issues.

We explain the moderating effects of risk factors on the linkages H1, H2, H3 and H4 with a graphical representation. The effects of the moderator risk factor, categorized by high risk factor and low risk factor on the linkages ADES→OPSC (H1) and ADES→SPSC (H3), are represented by two graphs in Fig. 3.

With an increase of ADES, there is an increase of OPSC (for H1) and SPSC (for H3) for the effects of low risk factors represented by dotted lines. In such a situation, there is a decrease of OPSC (for H1) and SPSC (for H3) for the effects of high risk factors represented by continuous lines. It appears that the effects of high risk factors impede operational and strategic public service to citizens. For both the graphs (Fig. 3), the gradients of the continuous lines are negative, and the gradients of the dotted lines are positive.

The effects of the moderator (high risk and low risk factors) on the linkages ABES→OPSC (H2) and ABES→SPSC (H4) are shown graphically (Fig. 4) where the lines represent the effects of high-risk factors and the broken lines represent the effects of low risk factors on linkages.

In both graphs, the gradients of the continuous and broken lines are negative and positive, respectively. It signifies that, with an increase of ABES, there is an increase of OPSC (for H2) and SPSC (for H4) for the effects of low risk factors. Again, with the increase of ABES, there is a decrease in OPSC (for H2) and SPSC (H4) for the effects of high-risk

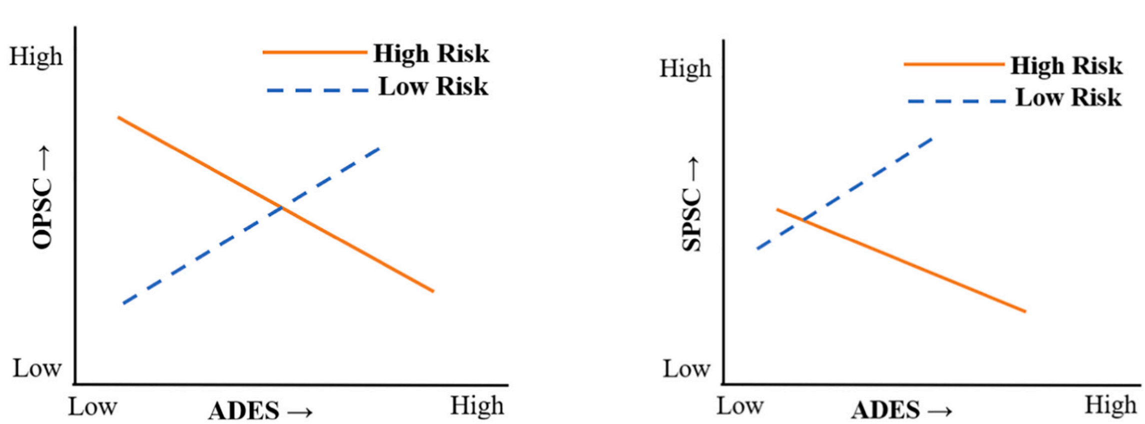

Fig. 3. Moderating effects of risk factor on H1 and H3.

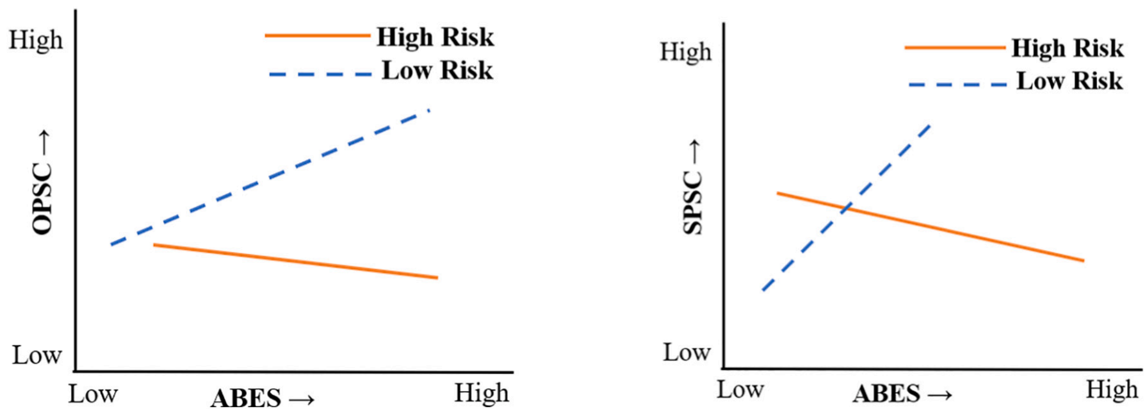

Fig. 4. Effects of the moderator on H2 and H4.

factors. The effects of low risk factors have a lower impact on operational and strategic public services, but the effects of high risk factors impede the progress of operational and strategic public services. The effect of the moderator risk factors for the four linkages H1, H2, H3 and H4 is found to be significant and confirms the Multi Group Analysis (MGA), shown in section 5.3.

6.1. Theoretical contributions

The theoretical contribution of this study is how AI-enabled government services are likely to foster the satisfaction of citizens. Earlier studies highlight the pre-adoption stage that focuses on enablers and barriers, and on benefits and risks, together with the identification of antecedents for AI-enabled government services (Mohammed, Ibrahim, Nilashi, & Alzurqa, 2017). Recent scholars focus on technology post-adoption stage for governmental organizations to examine how AI-enabled services create public value by assimilating technology (Wang et al., 2016). Others explore the antecedents of implementation after the adoption decision for a new technology in organizations (Sallehudin et al., 2016). However, detailed examination of IT assimilation in public value creation after the adoption stage, especially in the context of use of AI technology in governmental agencies, has been missing (Ali, Soar, & Shrestha, 2018), a gap that this paper addresses.

This study has successfully used the IT assimilation and public value theory to develop an integrative model that provides insights on how AI-enabled government services impact public value, in the form of deriving operational and strategic public services for enhancing citizens' satisfaction. This study draws on IT assimilation theory to explain how the simultaneous deployment of AI technology in terms of both breadth and depth assimilation impacts public value. We extend this concept by interpreting how the use of breadth and depth assimilation of AI technology by government departments creates public value for citizens. The public value theory explained how the creation of public value improves operational and strategic public service for citizens. This paper combines both theories to develop an integrated theoretical model that considers the impacts of risk factors as a moderator. We explore how governmental agencies create public value by delivering operational and strategic public services to citizens to achieve higher satisfaction with AI technology, which in the current context is not fully prevalent (Pang, Lee, & DeLone, 2014). Our model also addresses the gap in literature by examining the issue of organizational performance for the government sector in India and focuses in particular on AI technology assimilation. Sallehudin et al. (2016) highlight that the use of cloud computing has benefitted the public sector, an idea that our paper develops to consider how the use of AI technology can lead to benefits for the public sector.

Our study analyzes the issues of depth and breadth of assimilation of AI technology as two important building blocks to achieve operational and strategic success in public value by governmental agencies to enhance citizens' satisfaction. In addition, we extend the theoretical lens with a high predictive power by considering the issues of risk factors as a moderator that impacts the relationship between AI assimilation and public value to citizens.

6.2. Practical implications

This study shows that breadth assimilation affects operational public service for citizens (H2) and strategic public service for citizens (H4). In addition, depth assimilation impacts operational and strategic public service for citizens (H1 and H3). Furthermore, this study highlights that operational public service for citizens impacts strategic public service (H5). In this manner, the validated hypotheses provide several practical implications. Government agencies are recommended to use breadth assimilation for AI technologies; after the stakeholders have been acclimatized, government agencies should endeavor to achieve depth assimilation in government services. Such a move will not pose an impediment to users through breadth assimilation since they will be accustomed to using AI technology. Accordingly, it is important for governmental agencies to follow the norm 'easiness at first and difficulty in the latter stage'. This implies that the use of AI technology by government departments to discharge functions, including the analysis of data without human intervention, should commence with the application of technology on less complex issues. This will prepare the agencies to employ AI-related functions that are relatively easy to implement and can be easily deployed in coordination with different departments. The next step for government agencies is to migrate the complex and heterogeneous systems to AI-enabled systems. The hypotheses suggest that to achieve the full potential of breadth and depth assimilation of AI technology in governmental agencies, the use of AI technology in common functions is recommended across different government departments. This will support the government agencies to spread IT activities (breadth assimilation) followed by extending the use of AI technology in functions with special requirements.

Thus, for successful breadth assimilation, the governmental agencies should expand functions on the basis of 'ease at first, complex later' and 'common first and special later'. In this manner, government agencies will be able to implement the process of breadth assimilation systematically for ensuring operational and strategic performance for citizens. The governmental agencies are recommended to expand AI applications (breadth assimilation) followed by the promotion of omni-directional infiltration through depth AI technology assimilation in governmental units. In so far as the impacts of depth assimilation of AI on operational and strategic public services are concerned (H1 and H3), governmental agencies must try to penetrate depth assimilation through breadth assimilation of AI technology (H5). For this, governmental agencies are recommended to steer AI applications towards core business processes and roll out an in-depth AI technology application project to improve the quality of operational and strategic public service to enhance the satisfaction level of citizens.

6.3. Limitations and future research directions

Despite theoretical and practical contributions for the academic community and governmental agencies, this study suffers from limitations and therefore identifies areas for future research. The empirical investigation focuses on one country – India. Future researchers may conduct similar studies by using data from various countries to portray the overall picture. To study public value creation through improving operational and strategic public service for citizens, we relied on cross-sectional data analysis where the outcomes are limited to exploring the inter-temporal impacts of AI technology assimilation on the public value to affect operational and strategic public service for citizens. Future research may adopt different procedures to examine the longitudinal dynamics for creating public value using breadth and depth AI assimilation. The one-country concept cannot project the actual picture of governmental agencies on the use and outcomes of AI applications, which highlights the scope to use random measurement error (Ranganathan, Dhaliwal, & Teo, 2004).

7. Conclusion

AI technology implementation has been successful in the private sector for improving business value and developing the competitive advantage (Chatterjee, Nguyen, et al., 2020; Chatterjee, Rana, & Dwivedi, 2020). However, the adoption and use of modern technology in governmental agencies' activities is lagging (Liang et al., 2017). This study examines how AI technology through breadth and depth assimilation is likely to impact operational and strategic public services for citizens which, in turn, impact citizens' satisfaction positively. The strength of this study is the consideration of the risk factors that arise from flawed and biased algorithms, system malfunctioning, and a lack of knowledgeable and trained staff in government departments that pose privacy and security concerns. The model has been statistically validated with high predictive power (72.7%). However, since the use of AI technology in government sectors is in a nascent stage in India, this study is an initial attempt to theorize how governmental agencies can potentially harness AI technology to create public value. Our model is a baseline that can be used by different governments, and that can be extended in other contexts. The main findings of this study are that both depth and breadth assimilation of AI technology impact the operational performance of the government services provided to citizens. Further, the strategic performance of government services to citizens depends on the depth and breadth assimilation of AI technology. This paper highlights that the application of AI technology in government services can be fraught with risks if appropriate AI algorithms are not applied. Finally, use of appropriate AI technology in government services is likely to enhance citizens' satisfaction.

Appendix A. Summery of questionnaire

Items	Source	Statements	Response [SD] [D][N][A][SA]
ADES1	Lavie et al., 2010; Klein, 2012; Niehaves et al., 2013; Sallehudin et al., 2016;	We have fully adopted AI enabled services in our department.	[1][2][3][4][5]
ADES2	Chatterjee et al., 2019; Liang et al., 2019;	I believe that depth assimilation of AI technology improves the public services strategically.	[1][2][3][4][5]
ADES3		The AI technology has been extensively integrated with our services.	[1][2][3][4][5]
ADES4		I believe that depth assimilation of AI technology improves the operational efficiency of the public services.	[1][2][3][4][5]
ABES1	Hitt & Brynjolfsson, 1996; Bannister, 2001; Dong et al., 2009; Alford &	We have partially adopted AI enabled services in our department.	[1][2][3][4][5]
ABES2	O'Flynn, 2009; Zhang et al., 2016; Li et al., 2017; Liang et al., 2019	I believe that breadth assimilation of AI technology improves the public services strategically.	[1][2][3][4][5]
ABES3		There are only a few services that are now AI enabled.	[1][2][3][4][5]
ABES4		I believe that breadth assimilation of AI technology improves the operational efficiency of the public services.	[1][2][3][4][5]
OPSC1	Horan & Abhichandani, 2006; Niehaves et al., 2013; Liang et al., 2019; Chatterjee, 2019; Valle-Cruz et al., 2020	I think adoption of AI technology in public services could reduce the cost of operations.	[1][2][3][4][5]
OPSC2		I believe that integration of AI technology in public services could improve the efficiency of systems deployment.	[1][2][3][4][5]
OPSC3		Improvement of operational efficiency of public services could enhance strategic advantages.	[1][2][3][4][5]
OPSC4		I believe automation of public services could reduce the manual efforts and technological difficulty which could provide better operational efficiency.	[1][2][3][4][5]
SPSC1	Jaeger & Thompson, 2003; Kearns, 2004; Akman et al., 2006; Heeks, 2008; Alford & O'Flynn, 2009; Valle-Cruz et al., 2020; Zuiderwijk et al., 2021;	I think it is essential to fully integrate AI technology into public services to improve the citizens' experience.	[1][2][3][4][5]
SPSC2		I believe that real time reporting is possible once our services are fully integrated with AI technology.	[1][2][3][4][5]
SPSC3		Appropriate integration of AI technology into public services can improve service quality in the long term.	[1][2][3][4][5]
SPSC4		I believe that full integration of AI technology with the public services can improve citizens' satisfaction.	[1][2][3][4][5]
CS1	Jaeger & Thompson, 2003; Kearns, 2004; Akman et al., 2006; Horan & Abhichandani, 2006; Alford & O'Flynn, 2009; Chatterjee, 2019; Chohan et al.,	I believe citizens will enjoy better services once our services are fully integrated with AI technology.	[1][2][3][4][5]
CS2	2021; Zuiderwijk et al., 2021	Citizens like to use the applications which could provide them automated real-time updates.	[1][2][3][4][5]
CS3		We receive better feedbacks from citizens for the applications which are fully integrated with AI technology.	[1][2][3][4][5]
CS4		Applications of predictive analytics for the public services could improve the citizens' experience.	[1][2][3][4][5]
CS5		I believe that citizens can easily use AI enabled public services.	[1][2][3][4][5]

[SD = Strongly Disagree; D = Disagree; N = Neither agree nor disagree; A = Agree; SA = Strongly Agree].

Appendix B. Loading factors and cross-loading factors

Constructs/Items	ADES	ABES	OPSC	SPSC	CS
ADES1	**0.96**	0.17	0.35	0.32	0.19
ADES2	**0.92**	0.19	0.37	0.36	0.17
ADES3	**0.90**	0.31	0.39	0.31	0.31
ADES4	**0.95**	0.18	0.41	0.41	0.34
ABES1	0.17	**0.87**	0.27	0.17	0.35
ABES2	0.22	**0.94**	0.38	0.19	0.35
ABES3	0.36	**0.85**	0.21	0.32	0.37
ABES4	0.41	**0.87**	0.24	0.21	0.36
OPSC1	0.38	0.26	**0.95**	0.26	0.39
OPSC2	0.37	0.29	**0.89**	0.29	0.28
OPSC3	0.24	0.37	**0.94**	0.31	0.27
OPSC4	0.19	0.31	**0.92**	0.34	0.25
SPSC1	0.17	0.24	0.26	**0.95**	0.20
SPSC2	0.32	0.39	0.29	**0.95**	0.32
SPSC3	0.43	0.28	0.31	**0.96**	0.19
SPSC4	0.29	0.33	0.41	**0.90**	0.18
CS1	0.25	0.32	0.34	0.37	**0.85**
CS2	0.27	0.27	0.43	0.31	**0.96**
CS3	0.31	0.29	0.37	0.48	**0.87**
CS4	0.20	0.34	0.31	0.41	**0.92**
CS5	0.26	0.36	0.41	0.34	**0.85**

Note: The bold values indicate loading factors corresponding to the items.

Appendix C. Heterotrait–Monotrait (HTMT) Test

Constructs	ADES	ABES	OPSC	SPSC	CS
ADES					
ABES	0.37				
OPSC	0.39	0.32			
SPSC	0.31	0.26	0.24		
CS	0.27	0.19	0.31	0.19	

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