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Enabling AI capabilities in government agencies: A study of determinants for European municipalities

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ABSTRACT

Artificial Intelligence (AI) is gradually becoming an integral part of the digital strategy of organizations. Yet, the use of AI in public organizations in still lagging significantly compared to private organizations. Prior literature looking into aspects that facilitate adoption and use of AI has concentrated on challenges concerning technical aspects of AI technologies, providing little insight regarding the organizational deployment of AI, particularly in public organizations. Building on this gap, this study seeks to examine what aspects enable public organizations to develop AI capabilities. To answer this question, we built an integrated and extended model from the Technology-Organization-Environment framework (TOE) and asked high-level technology managers from municipalities in Europe about factors that influence their development of AI capabilities. We collected data from 91 municipalities from three European countries (i.e., Germany, Norway, and Finland) and analyzed responses by means of structural equation modeling. Our findings indicate that five factors – i.e. perceived financial costs, organizational innovativeness, perceived governmental pressure, government incentives, regulatory support – have an impact on the development of AI capabilities. We also find that perceived citizen pressure and perceived value of AI solutions are not important determinants of AI capability formation. Our findings bear the potential to stimulate a more reflected adoption of AI supporting managers in public organizations to develop AI capabilities.

1. Introduction

Artificial intelligence (AI) and its transformation potential have been a topic of much discussion both in literature and practice for decades (Dwivedi et al., 2021; Martínez-López & Casillas, 2013; Mikalef & Gupta, 2021). As technology has taken significant leaps in enabling AI development, AI is gaining momentum and becoming an essential part of organizational operations and everyday life (Desouza, Dawson, & Chenok, 2020; Raisch & Krakowski, 2021). While the development of AI technologies accelerates, the interest in AI and the adoption of the different AI technologies has grown (Duan, Edwards, & Dwivedi, 2019; Pan, 2016). AI can be characterized by being a system that mimics cognitive function and can perform carry out tasks with human-like and rational behavior (Russel & Norvig, 2015). AI technologies are used for example in the context of speech recognition, machine translation, computer vision, machine learning, and robotics (Eggers, Schatsky, & Viechnicki, 2017; Ransbotham, Gerbert, Reeves, Kiron, & Spira, 2018). These technologies hold a multitude of possible benefits depending on their application. For example, robotic process automation applications can improve accuracy, free resources, and reduced costs (Jovanović, Đurić, & Šibalija, 2018). Overall, AI applications are connected to the effectiveness of work, freed-up high-value work, and improved decision-making (Eggers et al., 2017), all of which can lead to improved organizational performance.

Owing to the potential benefits and diverse AI applications, AI is gaining attention both in private and public organizations. While the private sector has been ahead in this development (Ransbotham et al., 2018), AI technologies are now being adopted in public organizations as well (Desouza et al., 2020). In fact, there has been a growing discussion on the multitude of potential applications that AI solutions can offer for public administration (Wirtz, Weyerer, & Geyer, 2019). Nevertheless, there are many challenges that such public organizations must first

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overcome before being able to deploy novel AI into operations. Thus, it is not only important that technical challenges are resolved, but also that organizational planning is in place to accommodate AI-enabled changes. Such organizational planning entails that public organizations are aware of the coercing forces and constraints of the environment and are able to plan accordingly (Duan et al., 2019). The notion of an AI capability has recently emerged in the literature denoting the organizational capacity to leverage AI technologies to meet key objectives (Mikalef & Gupta, 2021). Based on the definition of the notion, organizations must foster complementary AI-related resources in order to be able to derive value from their investments. Yet, to date there is not much knowledge regarding how the internal and external environment of public organizations influences their ability to develop AI capabilities (Mikalef, Fjørtoft, & Torvatn, 2019a; Mikhaylov, Esteve, & Campion, 2018; Wirtz & Müller, 2018).

To study what aspects enable of inhibit public body organizations in developing their AI capabilities, we grounded this study on the Technology-Organization-Environment framework (TOE) in order to understand how different forces pertinent to the relevant categories shape outcomes. Specifically, we built on prior academic research that examined aspects that influence deployment and use of AI in public organizations, and put forward am integrated and extended model to explore their effects (Mikalef, Fjørtoft, et al., 2019a; Schaefer et al., 2021). To operationalize the study objectives, we developed custom-built questionnaire which was distributed to high-level IT managers in public organizations, in three different European countries: Germany, Norway and Finland. We focused specifically on municipalities as they represent important public organizations and offer a vast array of services to different stakeholders such as citizens, businesses, and other public organizations (Jakob & Krcmar, 2018). From a research point of view, we are still lacking a theory-driven understanding of how public organizations develop the capacity to leverage key technologies such as AI, and how aspects of the internal and external environment shape such capacities (Mikalef, Fjørtoft, et al., 2019a; Schaefer et al., 2021). From a practical perspective, public organizations are facing increasing pressure in improving efficiency and quality of service provision, particularly through the use of novel digital technologies (Akter, Michael, Uddin, McCarthy, & Rahman, 2020; Janssen & Van Der Voort, 2016; Urbach & Röglinger, 2019). In addition, for public organizations like municipalities to become more capable of deploying AI technologies and for government agencies to encourage the utilization of AI technologies, we must have a proper understanding of the main drivers of the deployment so that there can be support for these processes. Therefore, we put forth the following two research questions:

RQ1. *What factors affect public organizations to develop AI capabilities?*

RQ2. *How do these factors affect public organizations to develop AI capabilities?*

The rest of the paper is structured as follows. In the background section that follows, we describe the relevant academic literature of this study highlighting the need to look at AI capabilities of public organizations and introducing the TOE framework as a suitable lens in the study of factors that either enable or inhibit AI capability development. In Section 3, we present our research model and corresponding research hypotheses. In Section 4, we present the method we followed to actualize the study's objectives, followed in Section 5 by the empirical analysis and the outcomes. We conclude in Section 6 by discussing our findings from a research and practical standpoint and outline some key limitations that underpinned this study.

2. Related literature

2.1. Artificial intelligence capabilities

The notion of an AI capability is a relatively new one, following an accelerated use and adoption of AI technologies in the organizational context over the past few years (Mikalef & Gupta, 2021). The concept builds on a tradition of IS research towards capturing the capacity of organizations to leverage novel technologies, rather than solely identifying degrees of adoption of technical infrastructure (Conboy, Mikalef, Dennehy, & Krogstie, 2020; Handali et al., 2020). Specifically, IT capabilities, the concept on which AI capability is grounded, argues that organizations need to leverage technological as well as other complementary resources in order to realize value from new technology deployments (Bharadwaj, 2000; Liu, Ke, Wei, & Hua, 2013). Such conceptualizations of an organization's ability to leverage technology are more accurate representations of how much value can be expected, as they involved the intangible aspects that enable technological innovations to be put in action (Conboy, Dennehy, & O'Connor, 2020; Mikalef, Boura, Lekakos, & Krogstie, 2019; Wamba et al., 2017). The notion of an AI capability follows this logic, as it builds on the necessary technical and organizational elements required to effectively deploy AI resources towards prioritized objectives (Mikalef, Fjørtoft, & Torvatn, 2019b; Mikalef & Gupta, 2021).

In their recent study, Mikalef and Gupta (2021) define AI capabilities as "the ability of a firm to select, orchestrate, and leverage its AI-specific resources". This definition denotes that an AI capability goes beyond just selecting, or else adopting AI, and includes the capacity to bring AI-related projects to fruition. Grounded on the resource-based view (RBV) of the firm, an AI capability has therefore been conceptualized as being developed through the ability of organizations to foster complementary types of resources (Butler & Murphy, 2008) Specifically, several studies have distinguished between tangible, human, and intangible resources (Grant, 1991; Gupta & George, 2016). Building on this broad distinction, we follow the conceptualization of Mikalef and Gupta (2021) and argue that an AI capability comprises of complementary AI-related tangible, human, and intangible resources.

Grounded on conceptualizations from past literature, we argue that tangible resources include the data necessary to actualize AI algorithms, the technological infrastructure to support storage and transfer of data, as well as the processing power needed to run advanced AI techniques, and other basic resources such as financial flows (Desouza et al., 2020; Duan et al., 2019; Wirtz et al., 2019). In terms of human-related resources, AI capabilities require that organizations are able to both balance technical and management skills. Specifically, technical skills are necessary for handling data, and implementing AI techniques, while managerial skills for understanding what domain knowledge is required when developing AI applications and envisioning important areas for application (Dwivedi et al., 2021; Spector & Ma, 2019). Finally, the intangible resources required to foster an AI capability include the ability of organizations to carry out interdepartmental coordination, the capacity to initiate and carry out organizational change, as well as a proclivity for engaging in high-risk high-return projects (Davenport & Ronanki, 2018; Ransbotham et al., 2018; Sun & Medaglia, 2019). The combined presence of the previously mentioned resources is therefore argued to constitute a good measure of an organizations AI capability.

2.2. Artificial intelligence in public organizations

In public organizations, and particularly municipalities, the deployment levels of AI are still in a very early phase as documented by early empirical research (Mikalef, Fjørtoft, et al., 2019a). Being able to leverage AI in such contexts is subject to a number of different forces, and is hindered by political, legal and policy challenges (Dwivedi et al., 2021). As a result, there has been a renewed focus on digitalization of public organizations administration, and a call for more empirical research examining aspects that either promote or hold back AI utilization (Janssen, Brous, Estevez, Barbosa, & Janowski, 2020). Prominent examples of this move include the United States and China, which have been aspiring to take big steps in advancing the use of AI for public administration (Allen, 2019).

Prior studies focused predominantly on the technical aspects associated with the adoption of AI, placing significantly less research on the socio-organizational changes entailed with AI deployment. In other words, there is still a limited understanding of what aspects of the internal and external environment prompt public organizations to develop AI capabilities (Sun & Medaglia, 2019). Related studies have examined critical aspects of AI adoption, which places a greater emphasis on the related technological investments associated with AI (Schaefer et al., 2021). While AI adoption is a necessary first step, it has the limitation that it does not provide a complete picture of the organizational capacity to effectively manage and leverage AI technological and complementary resources towards the generation of organizational value (van Noordt & Misuraca, 2020).

In effect, AI adoption precedes the development of an AI capability, as the latter needs to be fostered and matured by the organization through a gradual process. Aligning to our research question, research on factors enabling the development of AI capabilities is at an inaugurating state. Smit, Zoet, and van Meerten (2020) argue that in order to support the use of AI, organizations must embrace 22 principal categories of ethical values (e.g., accountability, understandability, and equality) during the design of AI. Based on their findings, they proposed design principles for each category to improve AI design and execution. Although this work provides some very relevant guidelines for the development of AI applications in accordance with ethical design principles, it does not explain how organizational organizing around AI initiatives is developed to form AI capabilities.

2.3. Technology-organization-environment (TOE) framework

When new technologies emerge in the market, organizations and individuals tend to adapt their behavioral patterns to embrace them. The choice of acquiring and using a new invention or innovation, and the process by which a new technology spreads throughout a population is described together as technology adoption and diffusion (Hall & Khan, 2003). The diffusion phase of technology tends to be a lengthy process, as organizational, cultural, and legal issues require time to incorporate new adaptations (F. Lin, Fofanah, & Liang, 2011). Research has put forth a multitude of different technology adoption and diffusion models operating at different levels of analysis, from the individual, to the organizational. As this study investigates the capacity of municipalities to develop AI capabilities, theories that examine use of technology at the individual levels, such as the technology acceptance model (Davis, 1989), and the unified theory of acceptance and use of technology (Venkatesh, Morris, Davis, & Davis, 2003) are not suitable for the purpose.

As we look at the diffusion of AI in public organizations, the TOE framework provides a suitable theoretical framework as it allows for the inclusion of aspects pertinent to the internal and external environment that shape organizational assimilation patterns (Baker, 2012). The TOE framework allows us to differentiate between three important angles when studying technology diffusion: aspects relating to the technology itself, organizational factors, as well as important aspects of the environment (Hameed, Counsell, & Swift, 2012). The TOE framework has been one of the principal theoretical frameworks in the study of how organizations adopt and diffuse technology, primarily due to it being flexible to incorporate relevant contextual variables that are contingent upon the specific technology or organization that is been examined (Wang & Lo, 2016; Zhang, Zhao, Zhang, Meng, & Tan, 2017).

Due to the increasing relevance of AI in private and public organizations, the question of how AI can be incorporated into processes and organizations is becoming more and more important. As the TOE framework has been widely in studies of the adaptation of other disruptive technologies, such as big data (Bremser, 2018), cloud computing (Lian, Yen, & Wang, 2014), and business intelligence systems (Hatta, Miskon, & Abdullah, 2017), it provides a relevant orientation point for studies of AI in public organizations. In terms of the three main categories of factors that influence diffusion, the technological part describes the influences of perceptions of technology and the past experiences with utilization of digital solutions (Kuan & Chau, 2001). The organizational aspect of the framework refers to the internal organizing and the values and priorities of the organization as a whole (Salleh & Janczewski, 2016). Finally, the environment incorporates the external circumstances and conditions in which the focal organization operates (Wang & Lo, 2016).

To identify what aspects within these three broad categories, have an impact on the level of AI capabilities of municipalities, we survey past empirical work. Building on a qualitative research design, Schaefer et al. (2021) elicited perceived challenges regarding AI adoption through interviews with municipal employees in Germany. Following a survey-based study, Mikalef, Fjørtoft, et al. (2019a) identified some of the major challenges IT managers face in their attempt to integrate AI into their operations. Similarly, Wirtz et al. (2019) present a comprehensive overview of the challenges faced by public organizations during their efforts to leverage AI tools. A common denominator in these work points out to the fact the perceptions of managers regarding the potential value of AI are important drivers in their decision to deploy AI into operations. From the organizational perspective, managers point out that financial costs associated with AI as well as past experiences in developing innovative digital solutions are important elements in setting up the organizational elements surrounding AI. Furthermore, there is significant evidence hinting that aspects relating to perceptions of pressure from the government and citizens (Mikalef, Fjørtoft, et al., 2019a; Schaefer et al., 2021), as well as regulatory guidelines and incentives (Franzke, Muis, & Schäfer, 2021; Jensen, 2020) have an important conditioning effect on the levels of AI capabilities in municipalities. These early studies are used in the development of our research model and form the basis for the corresponding hypotheses that guide our research.

3. Research model and hypotheses

This section elaborates the factors used as enablers for the deployment of AI capabilities. The factors are structured aligned to the TOE-Framework in the following categories: technological, organizational, and environmental context. Based on these categories we derive seven hypotheses and present an integrated and extended model for factors enabling the development of AI in municipalities (cf. Fig. 1). The choice of relevant factors within each of the three categories was done based on the current accumulated knowledge in past research. The hypotheses examine the role of each underlying factor regarding its effect on an AI capability in municipalities. While these factors may not be exclusive, they represent some of the most noted aspects that shape municipal capacities to leverage AI towards organizational goals. We therefore develop an argumentation about the effect of each on the overall levels of AI capabilities for municipalities.

3.1. Technological context

The dimension of "perceived benefits" can be found in the existing literature by Kuan and Chau (2001) who also employed the TOE framework. For example, in their study on the adoption of electronic data interchange (EDI) in small businesses, they presented a perception-based model in which they distinguish between perceived direct and indirect benefits. In our study we define perceived benefits, aligned to the conceptualization of Kuan and Chau (2001), as the benefits that are perceived rather than the benefits that are delivered or enabled by technology. The term "direct" relies to operational advantages. Therefore, perceived direct benefits lead to an increase in performance of daily internal processes of an organization. However, perceived indirect benefits describe "perceived benefits rather than benefits that are actually provided" (Kuan & Chau, 2001) by technology. The term "indirect" refers to the benefit's strategic characteristics, meaning that

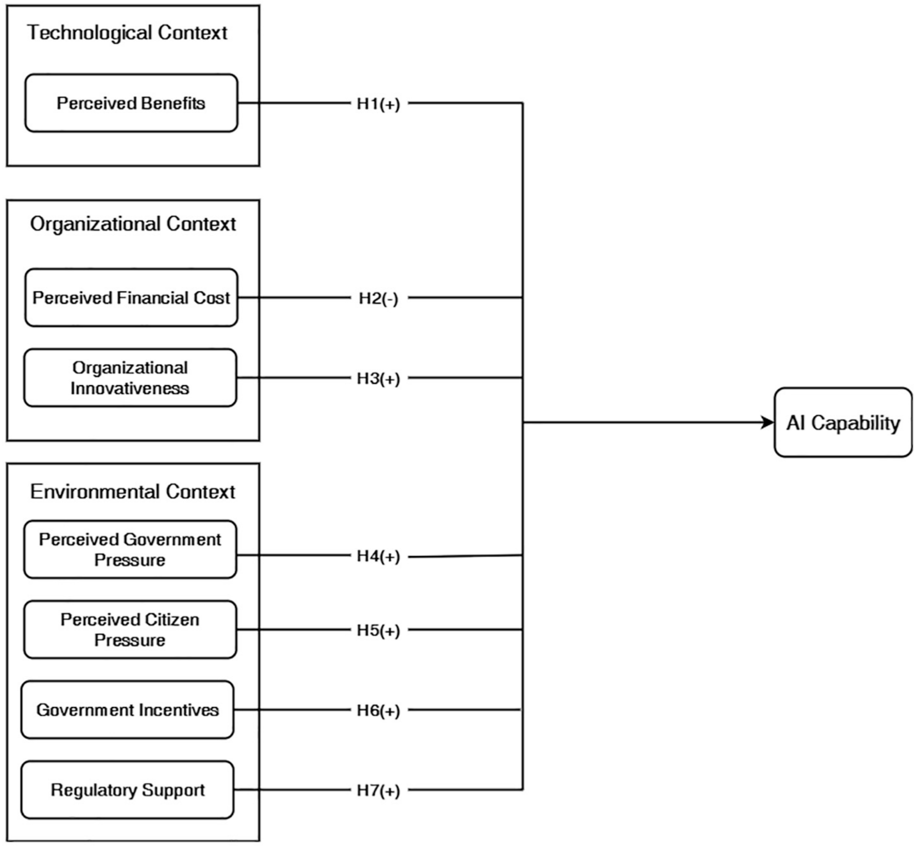

Fig. 1. Research model and hypotheses.

benefits are caused by external relationships with diverse stakeholders.

Previous literature provided information about how perceived benefits formed an incentive for the adoption or use of technology (Cruz-Jesus, Pinheiro, & Oliveira, 2019). The main rationale in the context of municipalities is that IT managers have a strong impact on the decision of municipalities to adopt AI and eventually to develop a strong AI capability. This decision, is largely shaped by their perceptions of the value that can be extracted from such investments, and their overall impression of the potential changes that AI technologies can introduce to their organizations (Mikalef, Fjørtoft, et al., 2019a; Schaefer et al., 2021). This leads us to hypothesize the following:

H1. *Perceived benefits will positively affect the development of AI capabilities.*

3.2. Organizational context

Perceived financial costs is a commonly used construct which can be found in past literature regarding the adoption of diverse technologies (Baker, 2012). Taking a manager's or employee's perspective demonstrates that costs can be perceived from a different point of view. Financial costs can be perceived from key decision-makers are barriers of adoption, especially when it is difficult to assess the degree to which new digital solutions will be able to generate measurable value (Kuan & Chau, 2001).

Because public organizations are financed by governmental funding and taxation, the average public organization has restricted budgets which do not allow for complete liberty in planning novel technology deployments (Misuraca, van Noordt, & Boukli, 2020). To implement new technologies in public organizations, supporting services and working processes for managers, employees and citizens are often calculated with a high amount of costs. Investing in the developing and implementing does not only cause direct financial costs but also overhead and personnel costs. As many public organizations struggle to implement new technologies, due to the perceived financial expenses, we hypothesize the following:

H2. *Perceived financial costs will negatively affect the development of AI capabilities.*

Transferring organizational innovativeness back to theory shows that openness is an important adoption decision factor which is described as *"the degree to which an organization is willing to infuse innovation"* (Lai & Guynes, 1994; Oliveira & Martins, 2010). The notion of organizational innovativeness has been used to understand the proclivity and cultural norms linked to specific organizations, and how it influences their decision to embrace technological innovations (Aboelmaged, 2014). Recent literature also describes organizational innovativeness as an enabler of adoption processes of new technologies, and especially AI technologies (Misuraca et al., 2020; Smit et al., 2020). Organizations that embrace a culture of innovativeness have been suggested to be more open to experiment with new ideas and technologies, and to provide more time and resources for trialing new solutions using novel tools (J. Lin, Luo, & Luo, 2020). From the foregoing argumentation we hypothesize the following:

H3. *Organizational innovativeness will positively affect the development of AI capabilities.*

3.3. Environmental context

The dimension of "perceived government pressure" is argued by Kuan and Chau (2001) to be an important environmental factor that prompts the adoption of technology. Top government bodies such as ministries tend to publish strategic goals in terms of digitalization goals, which is likely to result in perceptions of pressure to IT managers at the municipal level. The logic argues that IT managers will perceive a need to align their activities with those of national strategies, and that specific key indicators will need to be attained to satisfy goals (Mikalef, Fjørtoft, et al., 2019a). Decisions undertaken by governments can put municipalities under pressure regarding the organization of timeframes, financial costs, personnel issues, and process optimization (Wirtz & Müller, 2018). In addition, municipalities often follow such governmental pressure with undertaking different forms of resource configurations in order to meet governmental requirements. In the case of AI capabilities this can mean starting to develop the appropriate organizational structure, making data available and accessible, and developing pilot infrastructure to execute AI projects (Andreasson & Stende, 2019). Thus, we propose:

H4. *Perceived government pressure will positively affect the development of AI capabilities.*

In their study on the adoption of electronic government services, Tung and Rieck (2005) used the effect of "social influence" as an important factor in adoption decisions. The term defines the importance of the public's view of a company as it tries to influence the decisions undertaken by the organization. Since opinions of citizens and their needs are important to the municipalities they belong, the perceived pressure from society results in citizens providing pressure on municipalities in order to adopt novel technologies and provide better and more efficient services (Schaefer et al., 2021). Municipalities in particular have an important role in providing services to citizens, so it is highly probable that perceptions of pressure from the public is likely to nudge IT managers to accelerate their deployments (Bullock, Luccioni, Pham, Lam, & Luengo-Oroz, 2020). Thus, we propose that municipalities need to adapt to their citizen's needs, leading to perceived citizen pressure influencing municipalities deployment of AI capabilities. Thus, we hypothesize the following:

H5. *Perceived citizen pressure will positively affect the development of AI capabilities.*

Governmental incentives can be described as instigators for municipalities to deploy AI solutions as they provide the necessary resources to develop and deploy new technologies into operations (Komninos, 2006). As municipalities are dependent upon governmental support in developing new directions in terms of technological diffusion, the level of support that they receive is likely to have an important impact on the degree to which they foster AI (Misuraca et al., 2020). Apart from providing the relevant resource, governments oftentimes also offer incentives to continue the pursuit of important objectives. Such incentives are predominantly associated with financial benefits enabling the implementation of new technologies or the hiring of qualified personnel managers and employees to public organizations (Misuraca et al., 2020). Regarding the implementation of new technologies, both financial support and qualified managers and employees are important for municipalities during digital transformation processes (Niehaves, Röding, & Oschinsky, 2019; Schaefer et al., 2021). This leads us to hypothesize the following:

H6. *Government incentives will positively affect the development of AI capabilities.*

Prior literature argues that regulatory supports for municipalities has important effects on their decision to adopt and rollout digital solutions to the public (Androutsopoulou, Karacapilidis, Loukis, & Charalabidis, 2019; Pedersen, 2018). Regulatory support can be achieved for example through the regulations, strategies, and standards provided by higher hierarchical public organizations on different municipal levels. As municipalities aim to formulate regulations governance schemes in the absence of clear regulations for themselves on their own (Niehaves et al., 2019), regulatory supports from higher municipal levels can provide the needed support for municipalities to guide their actions in terms of digital transformation (Kane, Palmer, Phillips, Kiron, & Buckley, 2015). For example, recent literature in theory and practice refer to regulatory supports such as digital transformation strategies and AI strategies (Misuraca et al., 2020). Such initiatives are supposed to support municipalities regarding their own regulations and strategies by helping them to align to higher hierarchical supposed goals. We suggest that the presence of strong regulatory support will facilitate municipalities to foster their AI capabilities. We therefore hypothesize the following:

H7. *Regulatory support will positively affect the development of AI capabilities.*

4. Method

4.1. Survey administration and data

In this study we used a survey-based method to collect data from multiple municipalities in three different European countries. The choice of the method was based on the fact that survey-based studies allow for generalizability of outcomes and easy replication, and they enable the concurrent inclusion of several factors (Pinsonneault & Kraemer, 1993). In addition, survey-based studies are able to capture general tendencies and identify complex associations between variables in a sample. According to Straub, Boudreau, and Gefen (2004) survey-based research is also of importance for exploratory settings and for predictive theory to be able to generalize results. In this study, we use constructs and corresponding survey items that are largely based on previously published studies, so there is additional support for their psychometric properties. All constructs and respective items were measured on a 7-point Likert scale, a well-accepted practice in empirical research where there are no objective measures of hard-to-measure concepts like beliefs, attitudes, and capabilities (Kumar, Stern, & Anderson, 1993). Before the survey was deployed, a group of experienced researchers filled out the survey in order to verify that there were no errors and that all questions were clear and understandable. Due to the fact that we collected data from different European countries (e.g., Finland, Germany, and Norway), the survey was available in four languages (English, German, Norwegian, and Finish). The group of respondents of the pre-test noted sentences that were not clear so that translations could be refined. To achieve comparable insights, we collected data in three European countries that feature similarities with regards to their AI strategies and their AI progress Furthermore, all countries have in common a similarly revealed technology advantage (Ubaldi, 2020). Against this background, we expect the results to represent AI capabilities of public organizations in e-Government ready countries. A cross-country comparison did not reveal any significant differences regarding the core elements of our research model. This can be attributed to the fact that all three countries have very similar expenditure in public administration budgets as percentages of gross domestic product (GDP), and particularly in terms of budgets directed towards digitalization (EC., 2021).

To examine the hypothesized relationship of our research model, email invitations were sent out with a link to the electronic survey to key respondents in municipalities within three European countries. The target respondents mainly comprised of chief digital officers and higher-level technology managers in municipalities. For all three countries, a mailing list directory was created for the municipalities of the country, and information about the best suited respondent was obtained through the publicly available data on their respective websites. If information on relevant respondents was not available on these websites, a request was sent to the general email address of each municipality asking for the contact details of respondents that fit the profile. From the initial invitation towards key respondents, three subsequent reminders were sent out to increase response rates. The data collection processes started in October 2020 and was concluded in early January 2021. The final sample consisted of 132 responses of which 93 were complete and usable for further analysis.

The responses came from municipalities that ranged from some that were rather small in terms of population (under 1000 citizens), to other that were quite large (over 300,000 citizens). The largest proportion of responses came from Norwegian municipalities that accounted for 71% of the sample, while Germany accounted for 22%, and Finland 7% respectively. In terms of the respondents' position, we were able to collect responses for employees holding key positions related to IT, such as chief digital officers, IT directors, and IT managers. Furthermore, most municipalities had relatively well-staffed IT departments, with most having more than 10 dedicated employees working on IT projects. In addition, a considerable subset of municipalities had a large number of employees in their IT departments (50+ employees). With regards to their use of AI, the largest proportion of companies had been using AI for approximately 2 years (35%), with a smaller percentage having experience with AI for over 3 years (Table 1).

Since the data we used for this study were collected from a single respondent at a single point in time, there is a possibility that it may be subject to bias. To account for such bias, we followed the guidelines of Podsakoff, MacKenzie, Lee, and Podsakoff (2003) and ran several analyses to determine if there was cause for concern regarding common method bias. We first conducted a Harmon one-factor tests on the eight main variables used in the study. The outcomes did not produce a unifactorial solution, with the maximum variance explained by any one factor being 21.9%. This outcome is a good indication that common method bias is not a major concern. In addition, we tested for goodness-of-fit, based on the suggestions of Tenenhaus, Vinzi, Chatelin, and Lauro (2005) through PLS path modeling. In our empirical analysis, the outcomes suggest that the model has an acceptable goodness-of-fit since it surpasses the lower limit of 0.36 as suggested by Wetzels, Odekerken-Schröder, and Van Oppen (2009). As a result, these tests confirm that our research model and the way we operationalized it are not subject to common method biases. As a further method of determining if biases exist in our sampling procedure, we performed some analyses to examine for the presence of nonresponse bias. Specifically, the profile of municipalities that participated in the study was compared with those of which we did not receive a response or incomplete responses were delivered (e.g., size, country). Through a chi-square analysis we found that there was no significant systematic response bias. Finally, we also compared early with late respondents in terms of different sample demographic characteristics and found no indication of differences that could signal the presence of biased data. In order to ensure internal validity, we has an inclusive selection process sending invitations to all municipalities, and followed the exact same procedures for administration and treatment so as not to introduce any effects. To make sure that external validity criteria were met, we used several inclusion criteria to the municipalities and respondents we contacted, such as making sure that they were using AI applications and that we followed the same understanding of the notion (Kar & Dwivedi, 2020).

Table 1
Descriptive statistics of the sample and respondents.

Factors	Sample ($N = 93$)	Proportion (%)
Country		
Norway	66	71%
Germany	21	22%
Finland	6	7%
Respondents position		
Chief Digital Officer (CDO)	61	65%
IT director	20	22%
IT manager	9	10%
Operations manager	3	3%
Municipality size (Number of citizens)		
1000–9999	16	17%
10,000–24,999	12	13%
25,000–49,999	27	29%
50,000–99,9999	22	24%
100,000–299,999	12	13%
300,000 +	4	4%
Department size (Number of employees)		
1–9	21	23%
10–49	44	47%
50–249	25	27%
250 +	3	3%
Length of AI use in municipality (Number of years)		
< 1 year	11	12%
1 year	18	19%
2 years	33	35%
3 years	23	25%
4 + years	8	9%

4.2. Measurements

The scales for the constructs used in this study were primarily adopted or adapted from prior studies and have therefore been tested on their psychometric properties. The constructs used the in the empirical study as part of the main research model were all presented in the form of statements and measured on a 7-point Likert scale, from 1 (strongly disagree) to 7 (strongly agree). In Appendix A we provide a summary of the items used form the constructs of the study.

Perceived direct benefits was developed as a first-order reflective construct, according to the study of Kuan and Chau (2001). Respondents were asked to rate how much they agree or disagree regarding the potential direct benefits of adopting AI for municipality-related operations. Five items were used to capture the construct.

Perceived financial cost was developed as a first-order reflective construct, and asked respondents to evaluate their beliefs about the associated costs of adopting AI in their organizations. The items were based on the study of Kuan and Chau (2001) and included questions on set-up, training, and running AI. In line with the other measurements, the items measured respondents' perceptions.

Organizational innovativeness measured the degree to which respondents perceive their organization to have a culture that encourages and pursues continuous innovation. The construct was developed based on adapted items from the studies of Venkatesh and Bala (2012) and Salleh and Janczewski (2016).

Perceived government pressure captured the degree to which respondents experienced that top government was prompting municipalities to adopt AI. Respondents were asked to evaluate the level to which they perceived that the government was introducing measures and regulations to accelerate AI deployment. The items used were adapted from the study of Kuan and Chau (2001).

Perceived citizen pressure measured the level to which municipalities experienced a push from the citizens to deploy AI-based services. The construct was developed as first-order reflective based on adapted items from several studies (Salleh & Janczewski, 2016; Venkatesh & Bala, 2012). Respondents were asked to evaluate the degree to which they perceived that citizens wanted municipalities to provide more AI services.

Government incentives captured the degree to which respondents believed there were adequate measures and initiatives launched by top government to facilitate adoption and use of AI in municipalities. The construct was developed as a first-order reflective construct based on three indicators that were adapted from prior studies (Kuan & Chau, 2001; Salleh & Janczewski, 2016).

Regulatory guidelines measured the degree to which respondents believed there were clear regulations and directives about how to handle different relevant facets of AI projects, such as data security and protections schemes, ethical frameworks, and clear legal frameworks on data protection and use. The construct was self-developed based on prior work that included interviews with key respondents in municipalities and operationalized as a first-order reflective construct.

AI capability was adopted from the study of Mikalef and Gupta (2021) with minor adaptation to fit the case of municipalities. The construct captures the degree to which municipalities are able to leverage their AI-related resources. It is a third-order formative construct, comprised of eight first-order constructs.

5. Analysis

To actualize the study's objective and to determine the research model's validity and reliability, we built on partial least squares-based structural equation modeling (PLS-SEM) analysis. To run the analysis, we used the software package SmartPLS 3 (Ringle, Wende, & Becker, 2015) The choice of PLS-SEM is considered appropriate for this study since it allows the simultaneous estimation of multiple relationships between one or more independent variables, and one or more dependent variables (Akter, Fosso Wamba, & Dewan, 2017; Hair Jr & Hult, 2016). In contrast with other structural equation methods, PLS-SEM provides the advantage of (i) flexibility with respect to the assumptions on multivariate normality, (ii) use of both reflective and formative constructs, (iii) being able to compute complex models with smaller samples, (iv) allowing for robust estimation of formative constructs, and (v) allowing functionality as a predictive tool for theory building (Nair, Demirbag, Mellahi, & Pillai, 2018).

The use of PLS-SEM is widespread in the domain of information systems (IS) research, and specifically with regards to the estimation of complex relationships between constructs (Ahammad, Tarba, Frynas, & Scola, 2017; Akter et al., 2017; West, Hillenbrand, Money, Ghobadian, & Ireland, 2016). Furthermore, one of the advantages of PLS-SEM is that it allows for a calculation of indirect and total effects, which permits the simultaneous assessment of the relationships between multi-item constructs while reducing the overall error (Akter et al., 2017; Astrachan, Patel, & Wanzenried, 2014). In addition, the 93 responses analyzed as part of this study exceed both the requirements of: (1) ten times the largest number of formative indicators used to measure one construct, and (2) ten times the largest number of structural paths directed at a particular latent construct in the structural model (Hair et al., 2011). Lastly, since the research model is based on an exploratory study rather than a theory exploration, PLS-SEM is deemed as a more suitable alternative than covariance-based SEM.

5.1. Measurement model

Since our suggested research model includes reflective and formative constructs, we employed different assessment criteria to evaluate each. Furthermore, we included additional analyses for the higher-order construct used in the study (i.e., AI capabilities). The first step on the assessment of the measurement model was to assess the statistical properties of first-order reflective latent constructs. For these constructs we examined their reliability, convergent validity, and discriminant validity. We assessed reliability at the construct and item levels. For the former, we looked at the values of Composite Reliability (CR) and Cronbach Alpha (CA) and ensured that they were above the lower threshold of 0.70 (Nunnally, 1978). For the latter, we examined construct-to-item loadings, making sure that all were above the lower limit of 0.70 on their assigned construct (Appendix B). In gauging convergent validity, we used the Average Variance Extracted (AVE) values computed by SmartPLS to determine if all constructs surpassed the threshold of 0.50. The lowest observed value for first-order reflective constructs was 0.54, thus verifying that convergent validity was established. We examined discriminant validity by examining if each indicator loading was greater than its cross-loadings with other constructs (Appendix B), and by performing a Heterotrait–Monotrait ratio (HTMT) analysis (Henseler, Hubona, & Ray, 2016). All values in the HTMT ratio were lower than 0.85 which indicates that discriminant validity has been established (Appendix C). The detailed results are presented in Table 2, suggesting that the first-order reflective variables are valid to work with and are good indicators of their respective constructs.

For first-order formative constructs (Table 3) we started by assessing the weights and significance of items onto their respective constructs. Based on the suggestions of Cenfetelli and Bassellier (2009), even though formative constructs are likely to have some indicators with nonsignificant weights, they should not be removed as long as there is

Table 3
First-order formative construct validation.

Construct	Measures	Weight	Significance	VIF
Data	DT1	0.072	$p > 0.05$	1.965
	DT2	0.214	$p < 0.001$	2.980
	DT3	0.119	$p > 0.05$	3.265
	DT4	0.568	$p < 0.001$	2.149
	DT5	0.260	$p < 0.001$	2.561
	DT6	0.191	$p < 0.001$	2.189
Technology	TC1	0.512	$p < 0.001$	2.533
	TC2	0.121	$p < 0.001$	3.067
	TC3	0.244	$p < 0.001$	2.682
	TC4	0.158	$p < 0.001$	1.370
	TC5	0.314	$p < 0.001$	1.207
	TC6	0.152	$p < 0.001$	2.633
	TC7	0.197	$p < 0.001$	2.579
Basic Resources	BR1	0.241	$p < 0.001$	3.201
	BR2	0.503	$p < 0.001$	2.536
	BR3	0.243	$p < 0.001$	2.963

Table 2
Assessment of reliability, convergent, and discriminant validity of reflective constructs.

	Construct	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Perceived Benefits	**0.90**														
2	Perceived Financial Cost	0.64	**0.96**													
3	Organizational Innovativeness	0.51	0.36	**0.89**												
4	Perceived Government Pressure	−0.05	−0.17	0.38	**0.87**											
5	Perceived Citizen Pressure	0.18	−0.16	0.32	0.41	**0.81**										
6	Government Incentives	0.40	0.35	0.26	−0.06	0.23	**0.92**									
7	Regulatory Guidelines	0.12	0.18	−0.13	−0.16	0.06	0.43	**0.93**								
8	Data	0.22	0.28	0.43	0.12	0.25	0.38	−0.36	**n/a**							
9	Technology	0.56	0.55	0.56	0.05	0.14	0.39	−0.30	0.83	**n/a**						
10	Basic Resources	0.49	0.49	0.46	−0.18	0.10	0.51	−0.32	0.82	0.87	**n/a**					
11	Technical Skills	0.56	0.52	0.38	0.13	0.11	0.46	−0.19	0.68	0.88	0.69	**0.88**				
12	Business skills	0.53	0.50	0.74	0.32	0.14	0.26	−0.19	0.63	0.83	0.66	0.71	**0.86**			
13	Inter-departmental Coordination	0.17	−0.08	0.64	0.64	0.45	0.08	−0.19	0.43	0.27	0.21	0.18	0.51	**0.88**		
14	Organizational Change Capacity	0.34	−0.02	0.66	0.52	0.57	0.09	0.02	0.27	0.25	0.21	0.10	0.53	0.75	**0.79**	
15	Risk Proclivity	0.42	0.36	0.71	0.33	0.27	0.16	−0.16	0.58	0.69	0.52	0.58	0.80	0.54	0.56	**0.90**
	Mean	4.65	4.50	3.83	3.99	4.72	2.54	3.14	2.85	3.36	2.41	2.43	3.10	4.63	4.75	3.61
	Standard Deviation	1.86	1.74	1.44	1.44	1.43	1.40	1.42	1.40	1.81	1.38	1.54	1.61	1.29	1.27	1.56
	AVE	0.80	0.92	0.76	0.75	0.66	0.84	0.86	n/a	n/a	n/a	0.77	0.73	0.78	0.63	0.82
	Cronbach's Alpha	0.94	0.96	0.87	0.71	0.80	0.91	0.95	n/a	n/a	n/a	0.96	0.95	0.95	0.88	0.89
	Composite Reliability	0.95	0.97	0.92	0.86	0.85	0.94	0.96	n/a	n/a	n/a	0.97	0.96	0.96	0.91	0.93

strong theoretical justification for their inclusion in the measurement model. We find that two items related to the Data first-order construct are nonsignificant (i.e., DT1 and DT3). Yet, since each of the items of the Data constructs captures important complementary aspects of the overall concept, we retain the two indicators with nonsignificant weights. Next, we examine the extent to which indicators of formative constructs may be subject to multicollinearity. For assessing potential multicollinearity issues, we examine variance inflation factor (VIF) values, making sure they were below the more conservative cut-off point of 3.3 (Petter, Straub, & Rai, 2007).

In sequence, and after having established that the lower-order items are good representations of the constructs they capture, we proceeded to ensure that second order and third order formative constructs were valid. We followed the same procedure, ensuring that the corresponding dimensions were statistically significant on their corresponding higher order construct, and that multicollinearity was not an issue by examining VIF values (Table 4).

5.2. Structural model

The results of our structural model from the PLS analysis are depicted in Fig. 2. In the figure, we present the explained variance of endogenous variables (R^2), the standardized path coefficients (β), as well as representation of significance levels of the hypothesized associations. The outcomes of the analysis are gauged by examining the examining coefficient of determination (R^2) values, predictive relevance (Stone-Geisser Q^2), and the effect size of path coefficients. We obtain the significance of estimates (t-statistics) through the bootstrapping algorithm of SmartPLS running an analysis with 500 resamples. As shown in Fig. 2, five of the seven hypotheses were found to be statistically significant. Specifically, we observe that the perceived benefits of AI do not have a significant impact on a firms AI capability ($\beta = 0.134$, $t = 1.399$, $p > 0.05$). On the other hand, organizational factors have an influence on the extent to which municipalities are able to foster their AI capabilities, with perceived financial costs ($\beta = 0.263$, $t = 2.359$, $p < 0.05$), and organizational innovativeness ($\beta = 0.323$, $t = 2.991$, $p < 0.01$) exhibiting positive and significant impacts. When looking at the impact of the environmental context, we find that perceived citizen pressure is the only factor not having a significant effect ($\beta = 0.078$, $t = 0.674$, $p > 0.05$). We do find, however, that perceived government pressure ($\beta = 0.188$, $t = 2.358$, $p < 0.05$), and government incentives ($\beta = 0.299$, $t = 3.016$, $p < 0.01$) both positively impact municipalities AI capabilities. Surprisingly, we find a significant negative effect of regulatory guidelines on an AI capability which goes against our hypothesis ($\beta = -0.398$, $t = 3.545$, $p < 0.01$).

The structural model explains 72.4% of variance for AI capabilities ($R^2 = 0.724$). The coefficient of determination is extremely high, showcasing that the factors we have included in our analysis are important aspects in affecting the degree to which municipalities are able to foster their AI capabilities (Hair Jr, Hult, Ringle, & Sarstedt, 2016). Furthermore, to further verify our results we assess the model in terms of the effect size f^2. In looking at the effect size f^2 values, we are able to determine the contribution of each of the exogenous construct's contribution to the outcome variables (AI capabilities) R^2. We find that five out of seven variables direct values being above the thresholds of either 0.15 or 0.35. These results enable us to conclude that the exogenous variables have moderate to high effect sizes. To verify the effect of confounding, we also assessed the impact that control variables have on the AI capability of municipalities. As shown in Fig. 2, the influence of the control variables we included is found to be non-significant.

While the outcomes provide empirical support for some of our proposed relationships, we find that two are non-significant, and another two go against our theorizing. Specifically, we find that perceptions of the benefits of AI have no impact on whether a municipality will develop an AI capability. This outcome can be understood by the fact that there are likely other aspects that exert a stronger impact on ability of municipalities to develop an AI capability, such as a culture for innovativeness and the right mix of incentives and push from higher government, which likely render perceptions of value as less important. Similarly, we find that perceived citizen pressure does not play a role in the degree to which municipalities develop their AI capabilities, indicating that the push from citizens is either not present yet, or is not an influential factor that can prompt municipalities to foster AI in their operations. Our results also indicate two surprising findings. First, we find that the perceived financial cost of AI is positively associated with the development of an AI capability. This finding indicates that an understanding of the associated costs involved with adopting AI does not act as a hindrance for adoption, but rather, indicates that technology managers are aware of the associated investments and are able to plan for them. Second, we find that governmental guidelines in terms of AI-related processes act negatively in the formation of an AI capability. This surprising finding can be attributed to the fact that AI guidelines operate in a restricting manner, imposing constraints in rolling out AI applications instead of providing a coherent framework that can aid AI maturation in municipalities. In the next section we discuss in detail the theoretical and practical implications of our findings.

Table 4
Higher-order formative construct validation.

Construct	Measures	Weight	Significance	VIF
Tangible	Data	0.402	$p < 0.001$	2.767
	Technology	0.557	$p < 0.001$	3.167
	Basic Resources	0.180	$p < 0.001$	2.863
Human	Managerial Skills	0.507	$p < 0.001$	2.039
	Technical Skills	0.573	$p < 0.001$	2.039
Intangible	Inter-Departmental Coordination	0.546	$p < 0.001$	2.382
	Organizational Change Capacity	0.342	$p < 0.001$	2.470
	Risk Proclivity	0.250	$p < 0.001$	1.527
BDAC	Tangible	0.370	$p < 0.001$	3.012
	Human	0.508	$p < 0.001$	3.133
	Intangible	0.261	$p < 0.001$	3.088

5.3. Predictive validity

Further to assessing R^2 values, we also look at the Q^2 predictive relevance of exogenous variables (Woodside, 2013). The predictive relevance score is a measure of how well values are reproduced by the model and its parameter estimates using sample re-use (Chin, 1998). This method is a combination of cross-validation and function fitting and calculates each construct predictive relevance by removing inner model associations and computing changes in the criterion estimates (q^2) (Hair, Sarstedt, Ringle, & Mena, 2012). Values of Q^2 that are larger than 0 are an indication that the structural model has strong predictive relevance. In contrast, values below 0 are a sign of low predictive relevance (Hair Jr et al., 2016). Our analysis shows that the only dependent variable that we have, AI capability, has a satisfactory predictive relevance ($Q^2 = 0.411$). As the rest of the constructs of the TOE framework are exogenous constructs, they do not have Q^2 predictive relevance scores. Further on this analysis, q^2 value are above the value of 0.35, indicating that the effect size of predictive relevance is high.

6. Discussion

In this study we have sought to understand the aspects that either enable or hinder the ability of municipalities to foster an AI capability. As an increasing number of municipal processes can now be replaced and improved using AI, understanding how to facilitate structured adoption and use is of great importance for being able to deploy such solutions and provide better services to citizens and businesses. To expand our understanding of this topic, we developed a research model that attempted to explore the impact that different technological, organizational, and environmental aspects have on public organization

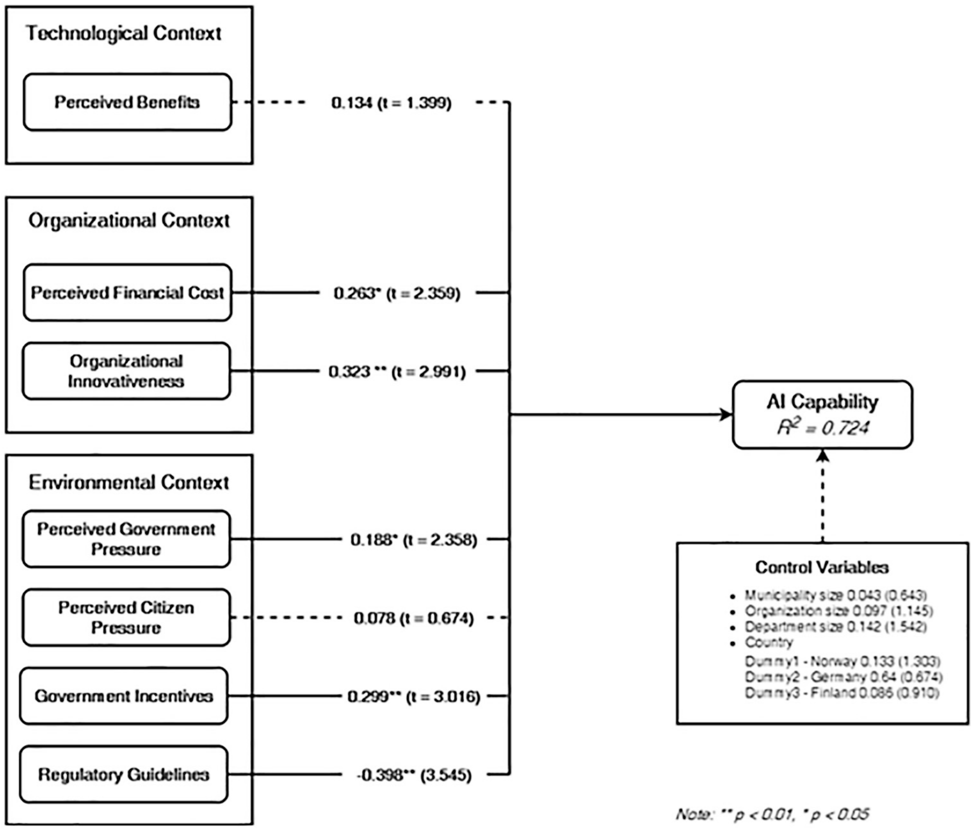

Fig. 2. Results of the PLS-PM estimation (β*** significant p < 0.01, β** significant p < 0.05, β* significant $p < 0.1$, n.s. = non-significant).

AI capability levels. We selected an AI capability as the outcome of interest, as it more accurately captures the ability of municipalities to leverage the relevant AI resources towards organizational goals. In contrast, simply examining AI infrastructure investments would not be a good measure of how ready municipalities are to implement AI applications. We therefore built on prior empirical work and used an adapted measure of an AI capability to determine what factors have an important bearing on a municipality's ability to leverage relevant AI resources towards key objectives. Using primary survey-based data from key respondents in 93 municipalities of three European nations, our results pinpoint to some interesting outcomes. In the next subsections we expand on the theoretical and practical relevance of these findings.

6.1. Implications for research

While the study of AI in organizations, particularly public ones, is still at a nascent level, research has started to examine applications of AI for public administration, as well as the supporting technologies required to deploy these (Wirtz et al., 2019). This study contributes to this direction by providing a more holistic perspective regarding AI leveragability (Akter et al., 2020). By introducing the notion of an AI capability for public organizations, and specifically municipalities, this work centers the importance not solely on the technological artifact, but on the ability of the organization to make effective use of it (Mikalef, Fjørtoft, et al., 2019a). In other words, the used notion of an AI capability more closely aligns with the concept of organizational readiness to deploy AI solutions to relevant stakeholders (Mikhaylov et al., 2018; Ransbotham et al., 2018). Expanding the perspective of AI beyond just data, infrastructure, and algorithms, our outcome variable encapsulates the necessary complementary resources that enable public organizations to generate AI applications that can be readily rolled out. We therefore add to the existing body of knowledge by studying how key organizational digital capabilities (i.e., an AI capability) are shaped and formed in their relevant context.

Second, while there have been some studies examining how internal, organizational aspects related to municipalities influence their levels of AI adoption and use (Schaefer et al., 2021; Wirtz et al., 2019), few studies so far have examined the concurrent effect of external pressures and influences. Drawing on the TOE framework, our study adds to the current body of research by investigating the competing enablers and inhibitors that influence AI capability levels in municipalities. By doing so, we consider internal characteristics such as perceptions of value and organizational innovativeness, as well as important aspects of the external environment. As top-government decisions have an important impact on actions of lower-level administration, it is important to understand how these forces coalesce to shape the AI capabilities of municipalities. In our study we also incorporate aspects relating to the perceived push from citizens and find some interesting results through our empirical analysis. The findings also reveal some surprising outcomes that generate further discussion about future research.

Specifically, we find that in the case of municipalities, the perceptions of senior-level IT managers on the value of AI have little impact on how much they are able to foster an AI capability. This finding can be attributed to the fact that an AI capability is not solely under the influence of the IT department and involves an organizational effort that requires synchronizations and planning from the top-down. In other words, to foster an AI capability, it is important that all departments are committed and are part of development efforts. This can be attributed to the fact that AI applications require data and input from domain experts that belong to different departments (Misuraca et al., 2020). It is therefore likely that organizational structure and decision-making appropriation play important roles in the ability of municipalities to build an AI capability. In addition, such an outcome may also mean that decentralizing decision-making and technology deployment in municipalities may not be an optimal solution when it comes to AI.

Our analysis also indicates some interesting results in relation to organizational factors that have an important role in shaping AI capabilities. We find support for the idea that innovativeness is associated with higher levels of AI capabilities, which confirms the understanding that the ability to make use of AI in municipalities is more associated with a general culture of adopting and embracing new ideas at an organizational level rather than at the individual level. This finding also shows that being able to prepare for leveraging AI is dependent on a prior developed capacity to innovate, which permeates the structure of the organization and sets some common values and targets. Furthermore, we find that perceptions of IT managers regarding the financial cost of AI to be associated with higher maturity of AI capabilities. This outcome can be explained by the fact that IT managers that have devoted the most time into planning their AI deployments are better aware of the incurred financial costs associated with such initiatives. As a result, IT managers that are able to develop a detailed plan for all costs before and during AI implementation, are also the most likely to have set in action the relevant resources to utilize such investments.

Finally, our analysis indicated some striking findings regarding the role of the external factors in shaping the levels of AI capabilities in municipalities. Specifically, we found that perceptions of citizen pressure do not have an impact on the level of AI capabilities developed internally. This can be explained in two different ways. First, that IT managers are not aware of opinions and attitudes of citizens regarding AI use for services that concern them, or do not have appropriate channels to communicate such opinions. Second, that the role of citizen-oriented AI applications is not on the primary list of objectives for many municipalities, that might seek more relevant and critical applications related to internal processes or interactions with other stakeholders. However, the other significant effect that we find points out to important facilitating and inhibiting forces. In detail, we find that perceptions of governmental pressure play a positive role in the development of an AI capability. This finding highlights that municipalities perceive that it is important to align with national strategies and directives regarding digital strategies, and particularly AI deployment (Niehaves et al., 2019). Furthermore, it suggests an important difference compared to private organizations where technology adoption is largely propelled by competition and costumer push (Dubey, Gunasekaran, Childe, Blome, & Papadopoulos, 2019).

In line with our argument, we also find that government incentives play an important role in developing AI capabilities. This outcome showcases the importance of not only providing some national strategies regarding AI deployment targets, but also following up with supportive measures to accelerate deployment and use of AI (Misuraca et al., 2020). In the case of municipalities that are public organizations, such incentives are very important, since they likely involve the required provision of cash flows and other resources needed to create strong AI capabilities. On the other hand, we find that regulatory guidelines have an impeding impact on the ability of municipalities to develop their AI capabilities. A potential explanation for this surprising finding can be that rules and regulations establish a strict operating framework which does not allow for the necessary flexibility and maneuvering to foster a municipal-wide AI capability. Such tight operating parameters can hinder the ability to access and use important data resources, for instance, or limit the transferability and re-use of existing important data sources.

6.2. Implications for practice

Apart from the contributions to the existing body of research, our study also points to some important practical implications that are of relevance for stakeholders at different levels. First, for IT managers in municipalities our findings suggest that they should consider the need to develop an organization-wide readiness perspective when deploying AI applications. Simply focusing on technology adoption through infrastructure investments and pools of data is unlikely to contribute towards value realization in AI-driven deployments. Furthermore, the findings underscore the importance of closely aligning organizational goals with managers of other domains in municipalities and fostering close ties of collaboration. Since AI applications require data and domain knowledge from different departments, it is important that there is a common understanding of the aims and goals of AI projects, and appropriate structures and processes have been put in action to accommodate these.

Furthermore, for senior administrative staff in municipalities the results show that it is important to balance both organizational aspects, such as a culture of innovativeness, with external relationships, such as negotiations with higher government bodies to ensure appropriate funding streams and regulatory frameworks that do not impede AI capability development. The issue of having access to sufficient governmental incentives for fostering AI capabilities is particularly heightened for smaller municipalities that most likely do not have the necessary additional resources required to foster AI alone. Furthermore, for such smaller municipalities having access to a sufficient quantity of data required to train AI applications is a major obstacle. Managers in such circumstances could opt for forming alliances or synergizing with other municipalities to co-create value and be able to enhance their AI capabilities.

From a policy-making point of view, it is important that strategic directions at a national level provide a sense of directions with specific goals that are relevant and attainable by municipalities when it comes to AI deployment. Furthermore, such directions need to be coupled with incentives that are aligned with the requirements of municipalities. Specifically, this means that the idiosyncratic requirements of different municipalities need to be considered, and appropriate aiding frameworks must be established to aid them in maturing their AI capabilities. Furthermore, in doing so it is important to have a clear understanding about what the main priorities and needs of citizens and relevant stakeholders in terms of AI-driven services are. Doing so will facilitate an alignment between the consumers and the providers of AI solutions, while ensuring that there are sufficient resources to foster required levels of AI capability within municipalities.

6.3. Limitations and future research

While our study contributes to the current body of research, it is not without limitations. First, the sample used in this study included only three countries in northern Europe, thus not being representative of the contingencies and contextual factors that may have an impact on public organizations in other countries. It is highly probable that in other countries, even within Europe, a completely different set of aspects may have an important influence on maturation of AI capabilities in municipalities. The three countries we collected data from in this study are largely homogenous in terms of availability of resources and socio-economic conditions. In countries characterized by economic austerity policies availability of incentives may not be present, and other forces may have an important impact on how municipalities develop their AI capabilities. Furthermore, differences in national cultures may have an impact on the types of enablers and inhibitors that are important (Gupta, Esmaeilzadeh, Uz, & Tennant, 2019). Second, in this study we collected data that correspond to a snapshot in time. This has the limitation that we cannot examine a process-perspective of AI capability maturation, and the dynamics that shape and form them over time. Furthermore, the sample from Finland was quite small compared to the other countries. While there are no expected large discrepancies between the three countries, future research could engage in a deeper cross-country comparison. Several additional internal and external aspects are therefore likely to emerge as inertial forces or key conditions in a municipalities ability to leverage AI effectively. Future studies can therefore focus on longitudinal studies to identify the evolution of such patterns of activity. Third, our analysis may likely not include other important factors that influence a national or regional level. For instance, distribution of authority between hierarchical levels of public administration may mean that in some countries there is greater liberty in crafting an AI strategy and implementing it in terms of an AI capability compared to others. An interesting future direction would therefore be to understand how the responsibilities assigned to municipalities play a role in their propensity to develop an AI competence.

7. Conclusion

In this paper we have sought to identify what factors affect public organizations to develop AI capabilities, and in sequence examine how these factors influence such an AI capability. The work has been motivated by the growing need for public organizations to move to AI-based solutions, and specifically to build in-house competences in deploying them. This requirement places an emphasis on fostering an AI capability, in order to be able to deploy AI solutions that improve the quality and efficiency of the provided services. In this work we have built on prior literature and on the TOE framework and isolated enablers and inhibitors of an AI capability. We theorize what type of effect these factors will have on the ability of public organizations to develop an AI capability, and empirically examine our hypotheses through a sample of 91 responses from IT managers in municipalities of three countries. Our results point out to several interesting findings regarding key enablers, as well as inhibitors. These outcomes provide some important implications for researchers in the quest of understanding how public organizations can generate value from novel digital technologies, as well as for practitioners and policy-makers in navigating the transition to the age of AI.

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Appendix A. Survey instrument

Measure	Item
Perceived Direct Benefits	PB1. We expect that the use of AI will help us to improve data accuracy
	PB2. We expect that the use of AI will help us to improve security of data
	PB3. We expect that the use of AI will help us to improve operation efficiency
	PB4. We expect that the use of AI will help us to speed up processing applications
	PB5. We expect that the use of AI will help to reduce clerical errors (e.g. duplicate data sets).
Perceived Financial Costs	PF1. The use of AI requires high set-up costs.
	PF2. The use of AI requires high running costs.
	PF3. The use of AI requires high training costs.
Organizational Innovativeness	OI1. My organization readily accepts innovations based on research results.
	OI2. Management in my organization actively seeks innovative ideas.
	OI3. Innovation is readily accepted in this organization.
	OI4. People are penalized for new ideas that do not work. (*dropped*)
Perceived Government Pressure	PG1. Progressive mandatory measures are introduced by the government (e.g. indexes to measure the number of digital services).
	PG2. Regulations regarding online services for citizens are established.
Perceived Citizen Pressure	PC1. Our citizens want us to provide our services digital.
	PC2. Our citizens ask for digital services on a regular basis.
	PC3. Our citizens prefer municipalities who provide digital services.
Government Incentives	GI1. There are enough motives available from top government and policy makers to ensure that AI initiatives can be implemented.
	GI2. There are enough financial resources available from top government and policy makers to ensure that AI initiatives can be implemented.
	GI3. There are enough governmental initiatives available to ensure that AI initiatives can be implemented.
Regulatory Guidelines	RG1. Government provides us an official ethical framework for the use of AI in municipalities.
	RG2. Government provides us official policies on the use of AI in municipalities.
	RG3. Government provides us official AI-policies on data security and protection in municipalities.
	RG4. Government provides us clarification of legal issues for the widespread and long-term use of AI in municipalities.
AI Capability	
Tangible	
Data	D1. We have access to very large, unstructured, or fast-moving data for analysis
	D2. We integrate data from multiple internal sources into a data warehouse or mart for easy access
	D3. We integrate external data with internal to facilitate high-value analysis of our business environment
	D4. We have the capacity to share our data across organizational units and organizational boundaries.
	D5. We are able to prepare and cleanse AI data efficiently and assess data for errors
	D6. We are able to obtain data at the right level of granularity to produce meaningful insights
Technology	T1. We have explored or adopted cloud-based services for processing data and performing AI and machine learning
	T2. We have the necessary processing power to support AI applications (e.g. CPUs, GPUs)
	T3. We have invested in networking infrastructure (e.g. enterprise networks) that supports efficiency and scale of applications (scalability, high bandwidth, and low-latency)
	T4. We have explored or adopted parallel computing approaches for AI data processing
	T5. We have invested in advanced cloud services to allow complex AI abilities on simple API calls (e.g. Microsoft Cognitive Services, Google Cloud Vision)
	T6. We have invested in scalable data storage infrastructures
	T7. We have explored AI infrastructure to ensure that data is secured from to end to end with state-of-the-art technology
Basic Resources	BR1. The AI initiatives are adequately funded
	BR2. The AI project has enough team members to get the work done
	BR3. The AI project is given enough time for completion
Human Skills	
Technical Skills	TS1. Our organization has access to internal talent with the right technical skills to support AI work
	TS2. Our organization has access to external talent with the right technical skills to support AI work
	TS3. Our data scientists are very capable of using AI technologies (e.g. machine learning, natural language processing, deep learning)
	TS4. Our data scientists have the right skills to accomplish their jobs successfully
	TS5. Our data scientists are effective in data analysis, processing, and security
	TS6. Our data scientists are provided with the required training to deal with AI applications
	TS7. We hire data scientists that have the AI skills we are looking for

(*continued on next page*)

(*continued*)

Measure	Item
	TS8. Our data scientists have suitable work experience to fulfill their jobs
Business skills	BS1. Our managers are able to understand business problems and to direct AI initiatives to solve them
	BS2. Our managers are able to work with data scientists, other employees and customers to determine opportunities that AI might bring to our organization
	BS3. Our managers have a good sense of where to apply AI
	BS4. The executive manager of our AI function has strong leadership skills
	BS5. Our managers are able to anticipate future business needs of functional managers, suppliers and customers and proactively design AI solutions to support these needs
	BS6. Our managers are capable of coordinating AI-related activities in ways that support the organization, suppliers and citizens
	BS7. We have strong leadership to support AI initiatives.
	BS8. Our managers demonstrate ownership of and commitment to AI projects.
	BS9. Our managers demonstrate an exemplary attitude to the use of AI.
Intangible	
Inter-Departmental Coordination	*Please indicate to what extent do departments within your organization engage in the following activities:*
	IC1. Collaboration
	IC2. Collective goals
	IC3. Teamwork
	IC4. Same vision
	IC5. Mutual understanding
	IC6. Shared information
	IC7. Shared resources
Organizational Change Capacity	OC1. Our organization is able to anticipate and plan for the organizational resistance to change.
	OC2. Our organization follows appropriate regulations when reengineering processes.
	OC3. Our organization acknowledges the need for managing change.
	OC4. Our organization is capable of communicating the reasons for change to the members of our organization.
	OC5. Our organization is able to make the necessary changes in human resource policies for process re-engineering.
	OC6. Our management commits to new values in our organization.
Risk Proclivity	RP1. In our organization we have a strong proclivity for high risk projects (with chances of very high returns)
	RP2. In our organization we take bold and wide-ranging acts to achieve firm objectives
	RP3. We typically adopt a bold aggressive posture in order to maximize the probability of exploiting potential opportunities

Appendix B. Cross loadings

	PB	PF	OI	PG	PC	GI	RG	D	T	BR	TS	BS	IC	OC	RP
PB1	**0.918**	0.563	0.381	−0.066	0.230	0.435	0.263	0.222	0.523	0.426	0.502	0.488	0.171	0.360	0.310
PB2	**0.914**	0.549	0.478	−0.115	0.167	0.324	0.078	0.216	0.536	0.448	0.485	0.403	0.123	0.272	0.386
PB3	**0.925**	0.615	0.490	−0.103	0.255	0.385	0.157	0.214	0.479	0.443	0.516	0.490	0.170	0.348	0.459
PB4	**0.939**	0.746	0.410	−0.162	0.088	0.484	0.092	0.263	0.596	0.586	0.629	0.503	0.021	0.223	0.346
PB5	**0.766**	0.330	0.530	0.256	0.028	0.135	−0.089	0.038	0.350	0.245	0.353	0.494	0.279	0.330	0.386
PF1	0.700	**0.953**	0.449	−0.157	−0.100	0.337	0.143	0.291	0.563	0.535	0.488	0.532	−0.043	0.134	0.471
PF2	0.564	**0.956**	0.263	−0.193	−0.095	0.329	0.182	0.299	0.547	0.473	0.530	0.452	−0.105	−0.123	0.268
PF3	0.543	**0.967**	0.288	−0.141	−0.288	0.330	0.207	0.206	0.465	0.394	0.460	0.437	−0.088	−0.102	0.268
OI1	0.579	0.446	**0.917**	0.203	0.328	0.291	−0.070	0.391	0.593	0.468	0.445	0.696	0.488	0.510	0.652
OI2	0.351	0.307	**0.867**	0.438	0.099	0.207	−0.121	0.404	0.462	0.416	0.239	0.717	0.601	0.651	0.668
OI3	0.414	0.178	**0.889**	0.399	0.422	0.195	−0.169	0.340	0.435	0.329	0.319	0.558	0.626	0.625	0.581
PG1	−0.074	−0.383	0.351	**0.839**	0.481	−0.031	−0.238	0.094	0.031	−0.153	0.092	0.184	0.589	0.435	0.238
PG2	−0.024	0.040	0.319	**0.897**	0.261	−0.072	−0.051	0.106	0.058	−0.160	0.129	0.361	0.530	0.474	0.322
PC1	0.147	−0.118	0.108	0.331	**0.774**	0.210	0.265	0.128	0.041	−0.045	0.003	0.055	0.356	0.487	0.039
PC2	0.195	−0.026	0.050	0.256	**0.763**	0.287	0.374	0.060	0.028	−0.026	0.016	0.011	0.201	0.390	−0.023
PC3	0.132	−0.175	0.401	0.381	**0.894**	0.150	−0.150	0.299	0.180	0.182	0.152	0.184	0.433	0.496	0.386
GI1	0.419	0.371	0.282	−0.142	0.116	**0.953**	0.308	0.455	0.489	0.623	0.552	0.316	0.053	0.096	0.206
GI2	0.358	0.236	0.251	−0.003	0.373	**0.949**	0.436	0.342	0.290	0.409	0.340	0.164	0.109	0.111	0.140
GI3	0.293	0.343	0.135	0.066	0.176	**0.845**	0.559	0.120	0.180	0.205	0.259	0.163	0.046	−0.003	0.000
RG1	0.133	0.302	−0.026	−0.082	0.011	0.320	**0.843**	−0.267	−0.124	−0.226	−0.022	−0.023	−0.147	−0.046	0.037
RG2	0.159	0.139	−0.131	−0.052	0.084	0.315	**0.949**	−0.418	−0.345	−0.400	−0.233	−0.200	−0.154	0.088	−0.162
RG3	0.095	0.218	−0.135	−0.211	0.006	0.482	**0.942**	−0.318	−0.256	−0.241	−0.166	−0.190	−0.203	−0.024	−0.174
RG4	0.067	0.115	−0.145	−0.214	0.084	0.456	**0.973**	−0.308	−0.297	−0.266	−0.201	−0.208	−0.201	−0.002	−0.193
D1	0.240	−0.021	0.354	0.373	0.302	0.051	−0.161	**0.712**	0.486	0.292	0.427	0.442	0.481	0.468	0.496
D2	−0.071	0.141	0.128	0.073	0.060	0.222	−0.295	**0.792**	0.577	0.551	0.444	0.269	0.206	−0.009	0.316
D3	0.218	0.104	0.291	0.135	0.308	0.148	−0.470	**0.775**	0.573	0.595	0.443	0.329	0.451	0.256	0.510
D4	0.297	0.270	0.480	0.135	0.244	0.346	−0.405	**0.918**	0.803	0.793	0.693	0.702	0.445	0.307	0.651
D5	0.013	0.134	0.287	0.100	0.269	0.303	−0.315	**0.812**	0.643	0.618	0.536	0.384	0.316	0.117	0.341
D6	0.369	0.399	0.315	−0.070	0.251	0.375	−0.164	**0.768**	0.590	0.745	0.394	0.421	0.344	0.324	0.388
T1	0.679	0.416	0.476	−0.038	0.237	0.402	−0.196	0.690	**0.852**	0.800	0.692	0.711	0.308	0.315	0.521
T2	0.289	0.340	0.458	0.181	0.276	0.140	−0.279	0.600	**0.728**	0.537	0.596	0.647	0.278	0.311	0.565
T3	0.181	0.456	0.427	0.056	−0.055	0.157	−0.271	0.589	**0.721**	0.604	0.510	0.638	0.079	0.178	0.551
T4	0.406	0.391	0.199	0.228	−0.032	0.268	−0.123	0.498	**0.724**	0.455	0.816	0.599	0.152	0.030	0.456
T5	0.360	0.433	0.301	0.199	0.013	0.211	−0.193	0.605	**0.779**	0.519	0.855	0.643	0.195	0.014	0.611
T6	0.137	0.240	0.404	0.111	0.105	0.253	−0.447	0.530	**0.750**	0.546	0.609	0.447	0.023	0.076	0.397
T7	0.481	0.574	0.422	0.067	0.019	0.429	−0.098	0.656	**0.796**	0.679	0.820	0.647	0.247	0.154	0.496
BR1	0.411	0.484	0.441	−0.095	−0.096	0.396	−0.344	0.698	0.795	**0.904**	0.592	0.648	0.158	0.158	0.489
BR2	0.384	0.373	0.244	−0.104	0.206	0.583	−0.175	0.634	0.716	**0.837**	0.641	0.505	−0.007	0.087	0.325

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(*continued*)

	PB	PF	OI	PG	PC	GI	RG	D	T	BR	TS	BS	IC	OC	RP
BR3	0.467	0.455	0.381	−0.169	0.185	0.568	−0.258	0.781	0.837	**0.968**	0.697	0.606	0.132	0.172	0.456
TS1	0.578	0.425	0.318	0.231	0.051	0.122	−0.296	0.368	0.628	0.383	**0.803**	0.520	0.174	0.118	0.351
TS2	0.477	0.719	0.328	−0.058	−0.045	0.461	−0.019	0.528	0.742	0.629	**0.791**	0.626	0.037	0.013	0.369
TS3	0.445	0.441	0.304	0.181	0.061	0.383	−0.230	0.644	0.816	0.618	**0.967**	0.664	0.185	0.014	0.578
TS4	0.404	0.370	0.233	0.198	−0.030	0.339	−0.328	0.544	0.714	0.545	**0.928**	0.544	0.112	−0.049	0.433
TS5	0.470	0.495	0.401	0.070	0.112	0.522	−0.181	0.799	0.899	0.777	**0.952**	0.712	0.204	0.098	0.643
TS6	0.431	0.390	0.322	−0.044	0.100	0.585	−0.017	0.701	0.812	0.752	**0.819**	0.677	0.214	0.170	0.548
TS7	0.614	0.388	0.340	0.190	0.291	0.460	−0.131	0.578	0.755	0.562	**0.861**	0.576	0.194	0.209	0.518
TS8	0.559	0.418	0.409	0.151	0.200	0.337	−0.160	0.583	0.808	0.540	**0.911**	0.687	0.125	0.147	0.611
BS1	0.210	0.166	0.716	0.588	0.279	−0.039	−0.321	0.512	0.576	0.340	0.484	**0.822**	0.639	0.556	0.793
BS2	0.243	0.127	0.698	0.554	0.396	0.100	−0.194	0.463	0.586	0.388	0.444	**0.845**	0.628	0.634	0.705
BS3	0.492	0.435	0.592	0.350	0.135	0.201	0.053	0.339	0.563	0.385	0.475	**0.825**	0.353	0.482	0.770
BS4	0.454	0.593	0.567	0.246	0.134	0.188	−0.129	0.540	0.731	0.562	0.641	**0.895**	0.268	0.361	0.647
BS5	0.495	0.390	0.692	0.232	0.343	0.314	−0.042	0.621	0.719	0.618	0.538	**0.890**	0.527	0.638	0.781
BS6	0.562	0.586	0.616	0.180	0.144	0.301	0.059	0.572	0.748	0.594	0.558	**0.859**	0.389	0.485	0.648
BS7	0.547	0.513	0.691	0.217	−0.093	0.288	−0.176	0.545	0.784	0.648	0.696	**0.917**	0.465	0.409	0.644
BS8	0.463	0.540	0.606	0.053	−0.157	0.339	−0.283	0.636	0.830	0.771	0.744	**0.861**	0.325	0.256	0.577
BS9	0.568	0.411	0.545	0.173	0.034	0.223	−0.389	0.574	0.795	0.647	0.831	**0.782**	0.400	0.326	0.650
IC1	0.221	0.042	0.547	0.549	0.457	0.205	0.015	0.399	0.309	0.205	0.217	0.470	**0.888**	0.656	0.417
IC2	0.198	−0.169	0.614	0.565	0.489	0.037	−0.207	0.401	0.241	0.173	0.122	0.431	**0.934**	0.687	0.482
IC3	0.152	−0.092	0.621	0.525	0.383	0.069	−0.218	0.436	0.248	0.246	0.125	0.480	**0.953**	0.716	0.489
IC4	0.273	−0.030	0.647	0.515	0.469	0.264	−0.157	0.431	0.356	0.330	0.320	0.551	**0.850**	0.724	0.522
IC5	0.092	−0.098	0.569	0.587	0.393	−0.103	−0.253	0.332	0.154	0.104	0.103	0.393	**0.853**	0.652	0.618
IC6	0.093	−0.002	0.566	0.644	0.295	0.019	−0.232	0.397	0.249	0.176	0.182	0.515	**0.921**	0.658	0.462
IC7	−0.056	−0.159	0.319	0.575	0.228	−0.050	−0.108	0.190	0.080	−0.006	−0.002	0.285	**0.754**	0.493	0.285
OC1	0.101	−0.318	0.384	0.385	0.419	−0.040	−0.265	0.224	0.090	0.126	0.000	0.258	0.709	**0.729**	0.301
OC2	0.329	−0.029	0.453	0.520	0.662	0.228	0.167	0.139	0.093	0.084	0.089	0.315	0.521	**0.792**	0.369
OC3	0.320	0.054	0.522	0.354	0.318	0.050	−0.077	0.179	0.216	0.225	0.100	0.424	0.507	**0.824**	0.339
OC4	−0.014	−0.155	0.228	0.286	0.569	0.188	0.320	0.055	−0.083	0.018	−0.198	0.120	0.453	**0.756**	0.278
OC5	0.370	0.189	0.667	0.301	0.292	0.030	0.127	0.262	0.383	0.246	0.218	0.598	0.439	**0.722**	0.598
OC6	0.433	0.117	0.786	0.575	0.457	0.011	−0.085	0.343	0.390	0.246	0.200	0.678	0.818	**0.907**	0.681
RP1	0.501	0.466	0.663	0.163	0.058	0.080	−0.186	0.500	0.690	0.498	0.605	0.744	0.475	0.323	**0.853**
RP2	0.358	0.359	0.710	0.323	0.332	0.239	−0.246	0.636	0.690	0.594	0.546	0.775	0.479	0.502	**0.939**
RP3	0.303	0.183	0.571	0.378	0.310	0.099	−0.021	0.431	0.504	0.338	0.446	0.665	0.502	0.660	**0.917**

Appendix C. Heterotrait-Monotrait ratio (HTMT)

	Construct	1	2	3	4	5	6	7	8	9	10	11	12
1	Perceived Benefits												
2	Perceived Financial Cost	0.656											
3	Organizational Innovativeness	0.563	0.373										
4	Perceived Government Pressure	0.215	0.304	0.510									
5	Perceived Citizen Pressure	0.236	0.175	0.335	0.530								
6	Government Incentives	0.410	0.368	0.267	0.138	0.352							
7	Regulatory Guidelines	0.161	0.222	0.144	0.234	0.342	0.502						
8	Technical Skills	0.593	0.540	0.410	0.197	0.170	0.448	0.200					
9	Business skills	0.556	0.506	0.812	0.413	0.247	0.258	0.210	0.733				
10	Inter-departmental Coordination	0.204	0.117	0.698	0.807	0.454	0.149	0.209	0.198	0.541			
11	Organizational Change Capacity	0.387	0.227	0.738	0.660	0.657	0.157	0.254	0.218	0.576	0.793		
12	Risk Proclivity	0.474	0.393	0.814	0.406	0.276	0.173	0.184	0.633	0.781	0.579	0.608	

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