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Examining how AI capabilities can foster organizational performance in public organizations

Patrick Mikalef[a,b,*], Kristina Lemmer[c], Cindy Schaefer[d], Maija Ylinen[e], Siw Olsen Fjørtoft[a], Hans Yngvar Torvatn[a], Manjul Gupta[f], Bjoern Niehaves[g]

[a] Department of Technology Management, SINTEF Digital, S P Andersens vei 3, 7032, Trondheim, Norway
[b] Department of Computer Science, Norwegian University of Science and Technology, Sem Saelands Vei 7, 7034, Trondheim, Norway
[c] Leuphana University Lüneburg, Institute of Information Systems Research, Fakulty of Management and Technology Universitätsallee 1, 21335, Lueneburg, Germany
[d] Institute of Business and Information Systems Engineering, University of Siegen, Germany
[e] Department of Industrial Management, Tampere University of Technology, Finland
[f] Department of Information Systems and Business Analytics, College of Business Florida International University, Miami, FL, USA
[g] University of Bremen, Bibliothekstraβe 1, 28359 Bremen, Germany

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ABSTRACT

Developing the capacity to digitally transform through AI is becoming increasingly important for public organizations, as a constantly growing number of their activities is now becoming AI-driven. This prompts an understanding of how public organizations should organize in order to derive value from AI, as well as in which forms can value be realized. Against this background, this paper examines how AI capabilities can lead to organizational performance by inducing change in key organizational activities. Using a survey-based study, we collected data from European public organizations regarding the indirect effect AI capabilities have on organizational performance. Data was collected from 168 municipalities from three European countries (Norway, Germany, and Finland) and analyzed by means of structural equation modeling. Our findings show that AI capabilities have a positive effect on process automation, cognitive insight generation, and cognitive engagement. While process automation and cognitive insights are having a positive effect on organizational performance, we found that cognitive engagement negatively affects organizational performance. Our findings document the key resources that constitute an AI capability and showcase the effects of fostering such capabilities on key organizational activities, and in turn organizational performance.

1. Introduction

Public organizations have started to digitally transform leveraging novel digital technologies such as Artificial Intelligence (AI), particularly over the last few years (Legner et al., 2017). Governments now realize that digitally transforming operations by means of AI is a necessity for public organizations in order for them to be able to deliver quality services to citizens and stakeholders (Misuraca, van Noordt, & Boukli, 2020). AI has been argued to enhance the ability of public organizations to respond to the quickly changing operational environment (Janssen & van der Voort, 2016) as well as improve the quality and speed of service provision to relevant parties (Douglas, Raine, Maruyama, Semaan, & Robertson, 2015; Mergel, Kattel, Lember, & McBride, 2018). A prominent such example is Australia's Taxation Office virtual assistant. "Alex", that can respond to >500 questions, and has engaged in 1.5 million conversations and resolved over 81% of enquiries at first contact. Nevertheless, recent reports and empirical studies showcase that many public organizations are struggling to leverage their AI applications, making it unclear how and if organizational value can be realized from such investments (Mikalef, Fjørtoft, & Torvatn, 2019). A recent report by Gartner (2021) highlights that although public organizations are increasing their investments in AI there are still some core areas that delay deployment. This poses an issue for researchers and practitioners regarding how they can leverage AI applications to achieve organizational goals, as well as how to document performance improvements.

While there is a plethora of successful cases of AI deployment in public and government organizations (Wirtz, Weyerer, & Geyer, 2019),

* Corresponding author.
E-mail address: patrick.mikalef@sintef.no (P. Mikalef).

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there is still a limited understanding of how public organizations can foster a capacity to readily deploy AI applications in areas that are critical for them. Recently, the notion of an AI capability has been put forth to describe the capacity of organizations to plan and deploy AI solutions in order to improve key organizational activities (Mikalef & Gupta, 2021). This notion builds on the idea that organizations must develop an appropriate bundle of resources in order to be able to leverage the potential of AI. Similarly, recent findings on the use of AI in public organizations highlights that the reason many of these entities are not deploying AI into operations is due to lacking resources or other organizational hurdles (Schaefer, Lemmer, & Kret, 2021). For instance, several studies note that public organizations are likely to face challenges when it comes to acquiring the necessary data to deploy AI, securing financial resources to invest in the necessary technological infrastructure, or are restricted by a lack of personnel and culture that does not promote digital transformation (Jensen, 2020; Mikalef et al., 2019; Mikhaylov, Esteve, & Campion, 2018; Wirtz et al., 2019).

To bridge this gap of knowledge, this study is builds on the notion of an AI capability, as a necessary capacity that public organizations must foster to realize value from the novel digital technologies. Grounded on the resource-based view (RBV) of the organization, we put forth an adapted operationalization of the notion which outlines three broad types of resources that need to be developed by public organizations: tangible, intangible, and human resources. We argue that AI capabilities exert an indirect effect on perceptions of organizational performance outcomes, by prompting changed in three key organizational activities. Specifically, we hypothesize that AI capabilities have effects on automating processes, increasing cognitive insight generation, and in enhancing cognitive engagement with citizens and employees. This work therefore adds to research by elucidating the key dimensions that public organizations need to develop to realize value from AI, and by empirically demonstrating the mechanisms through which organizational performance improvements can be realized. It also offers practitioners an understanding of how they should approach novel digital technologies such as AI, and pinpoints areas in which AI initiatives can be directed.

To actualize the objective of this study we developed a custom-build questionnaire and distributed it to Chief Digital Officers (CDOs) of public organizations in Germany, Norway, and Finland. Specifically, the questionnaire was sent to municipalities, as they have a vast potential to utilize AI applications in various types of services both to individual citizens as well as businesses and other public sector stakeholders (Jakob & Krcmar, 2018). By means of partial least squares structural equation modeling (PLS-SEM), we empirically explore our research model and corresponding hypotheses. The research questions that guide our investigation include the following:

RQ1: What is the effect of AI capabilities on organizational performance?

and

RQ2: Through what mechanisms are the effects of AI capabilities on organizational performance realized?

The rest of this paper is organized as follows. In the next section, the notion of an AI capability is presented along with related work on how it has been studies in the context of public organizations. In section 3 we present our research model and hypotheses, which is then followed by a description of the method we used to operationalize the objective of this research. Section 5 presents the results of the analysis, while in section 6 we discuss the theoretical and practical implications of this work and highlights some key limitations.

2. Background

2.1. Artificial intelligence capabilities in the public sector

AI technologies and applications differ from other technological advancements through their ability to mimic cognitive functions, perform tasks in a human-like manner and with the ability to learn and self-correct (Russell & Norvig, 2015). AI technologies have a variety of uses such as process automation, virtual agents, predictive analytics, recommendation systems, and speech analytics (Wirtz et al., 2019), all of which hold a variety of possible benefits. For example, they can free resources, improve accuracy, and reduce costs (Jovanović, Đurić, & Sibalija, 2019). Adoption of AI technologies in the public sector organizations, although increasing, is still in early stages (Mikalef et al., 2019). The initial empirical research on public sector AI adoption has focused on factors either driving or inhibiting the utilization of AI technologies, including factors such as political, legal and policy (Dwivedi et al., 2021), while the studies on how different public sector organizations could improve their ability to utilize these technologies and enhance organizational performance are still largely missing (Mikalef & Gupta, 2021; Sun & Medaglia, 2019). Some studies have shown that AI applications in public administration have a positive impact on perceived public service value (Wang, Teo, & Janssen, 2021), decision-making processes (Nasseef, Baabdullah, Alalwan, Lal, & Dwivedi, 2021), and in improving resource allocation (Valle-Cruz, Fernandez-Cortez, & Gil-Garcia, 2021).

However, for now, many organizations are struggling with the realization of the benefits AI technologies are expected to yield (Davenport & Ronanki, 2018; Ransbotham, Kiron, Gerbert, & Reeves, 2017). One explanation for this are the insufficient AI capabilities of organizations, which inhibit the organizations to identify, implement, and utilize suitable AI technologies. Consequently, through developing AI capabilities organizations could improve the realization of organizational performance (Mikalef & Gupta, 2021). In framing the notion of AI capability, we follow the definition of Mikalef and Gupta (2021) p. 2), who state that it is: "*the ability of a firm to select, orchestrate, and leverage its AI-specific resources*", meaning that, organizations with AI capabilities have the ability to leverage various AI technologies and create value from their utilization (Bharadwaj, 2000). This definition of AI capabilities is strongly grounded in RBV, which attempts to explain the relationship between organizational resources and their performance. In the context of capabilities, several RBV-based studies distinguish resources into tangible, human, and intangible resources (Grant, 1991; Gupta & George, 2016). From this categorization relying on the conceptualization of Mikalef and Gupta (2021), we define organizational AI capability to comprise elements of tangible, human, and intangible resources.

Following previous literature, we consider the tangible AI capability resources to include the organization's physical resources such as equipment and data necessary to run AI applications (Ransbotham et al., 2017) as well as other basic resources necessary to upkeep AI applications (Wirtz et al., 2019). The human-related resources then refer to AI capabilities necessary to develop and train AI applications as well as the ability to perceive the potential of AI technologies in different business contexts (Melville, Kraemer, & Gurbaxani, 2004). This encompasses technical skills including the ability to handle vast amounts of data and implement AI technologies as well as managerial skills that allow organizations to comprehend the different potential application of various AI technologies (Dwivedi et al., 2021). The AI capability-related intangible resources then include abilities such as interdepartmental coordination and organizational ability to initiate and implement change (Davenport & Ronanki, 2018; Ransbotham et al., 2017; Sun & Medaglia, 2019). Together these different resources are suggested to provide a sufficient measurement of organizational AI capability (Mikalef & Gupta, 2021).

2.2. Artificial intelligence capabilities and organizational performance

The value of AI on organizational performance has been discussed in several research commentaries and reports (Davenport & Ronanki, 2018). Nevertheless, despite substantial anecdotal claims regarding the value that AI can deliver to public organizations, there is limited empirical work to support such claims. More specifically, there is a lack of understanding on how public organizations need to organize around AI, as well as what type of value can be expected from such investments. In their recent work, Wirtz et al., 2019 present a series of applications of AI that are relevant for public organizations, along with some key challenges. These examples demonstrate that AI has the potential to prompt differences forms of organizational change. Davenport and Ronanki (2018) suggest that AI can deliver three distinct types of organizational impact: by automating processes, enhancing engagement with internal and external stakeholders, and by enabling the generation of novel insights. A number of studies have documented such isolated effects through specific types of AI applications. For example, Androutsopoulou, Karacapilidis, Loukis, and Charalabidis (2019) showcase how chatbots increase engagement between government and its citizens. Kouziokas (2017) finds that public organizations can generate value from AI by developing better forecasting approaches, which facilitates more accurate and actionable insight. Young, Bullock, and Lecy (2019) in their study document the effects AI can have in reducing bureaucratic processes and improving overall process automation. Nasseef et al. (2021) find that AI can improve knowledge around decision-making processes, thus enhancing the insight generation of key decision-makers in public organizations.

Despite the promising early findings of these studies, most work today either builds on single cases or is conceptual in nature. In addition, these studies do not analyze the different mechanisms of value generation concurrently. As a result, it is not easy to discern how public organizations should organize around AI, and what the overall effects on organizational performance are. The literature on AI capabilities argues that by fostering such organization-wide capacities, public organizations will be able to deploy different types of AI applications, that can in turn affect organizational performance through independent mechanisms (Mikalef et al., 2021). Effectively, AI capabilities enable public organizations to move beyond single applications of AI, to having the capacity of digitally transforming their operations in order to improve overall performance. The notion of an AI capability therefore assumes that public organizations will be more inclined to realize improvements in key organizational activities if they have developed the appropriate AI resources (Matheus, Janssen, & Janowski, 2021; Sharma, Luthra, Joshi, & Kumar, 2021). In turn, such organizational impacts will indirectly affect organizational performance indicators that are important for public organizations (Shareef et al., 2021). It is therefore argued that AI capabilities exert indirect effects on organizational performance indicators, by prompting changes in organizational activities.

3. Research model and hypotheses

In this section we develop our research model and hypotheses, in which argue that AI capabilities exert an indirect effect on organizational performance, by prompting change in organizational activities. Aligned with the work of Davenport and Ronanki (2018), the effect of AI capabilities is suggested to be exercised on process automation, cognitive engagement, and cognitive insight. Our argumentation suggests that AI capabilities will influence performance by prompting changes in the three underlying activities, which in turn positively affect organizational performance. Based on the above, we derive six hypotheses and present a research model for value generation through AI (c.f. Fig. 1). In the hypotheses we examine the impact that an AI capability has on process automation, cognitive engagement, and cognitive insight. In this regard, AI is assumed to prompt changes in the efficiency and effectiveness of using digital technologies to support key operations. These organizational impacts are in turn hypothesized to improve organizational performance indicators that are important for public organizations.

In general, the literature has recognized that organizations with adequate abilities to utilize AI technologies can benefit from AI in three ways, by utilizing new technologies in process automation, by enhancing their data analysis and gaining actionable insight, and by increasing engagement of customers and employees (Davenport & Ronanki, 2018). Overall, these three areas represent complementary aspects that enhance overall organizational performance in different ways.

First, by fostering AI capabilities, organizations are argued to become better equipped to identify suitable application targets for tools such as robotic process automation and be able to implement and upkeep these types of tools (Willcocks, Lacity, & Craig, 2017). In addition, applications such as natural language processing have been argued to enable automation of manual processing of documents, thus leading to efficiency gains and reduction of process bottlenecks (Wirtz et al., 2019). In addition, tasks such as data entry, checking documents requirements, processing applications forms, as well as other manual tasks can be automated by deploying appropriate AI solutions (Al-Mushayt, 2019). This however poses a requirement on public organizations to develop AI capabilities in order to identify such manual processes that tie up human resources and automate them by means of AI. Thus, we propose:

H1. AI capabilities will have a positive effect on process automation.

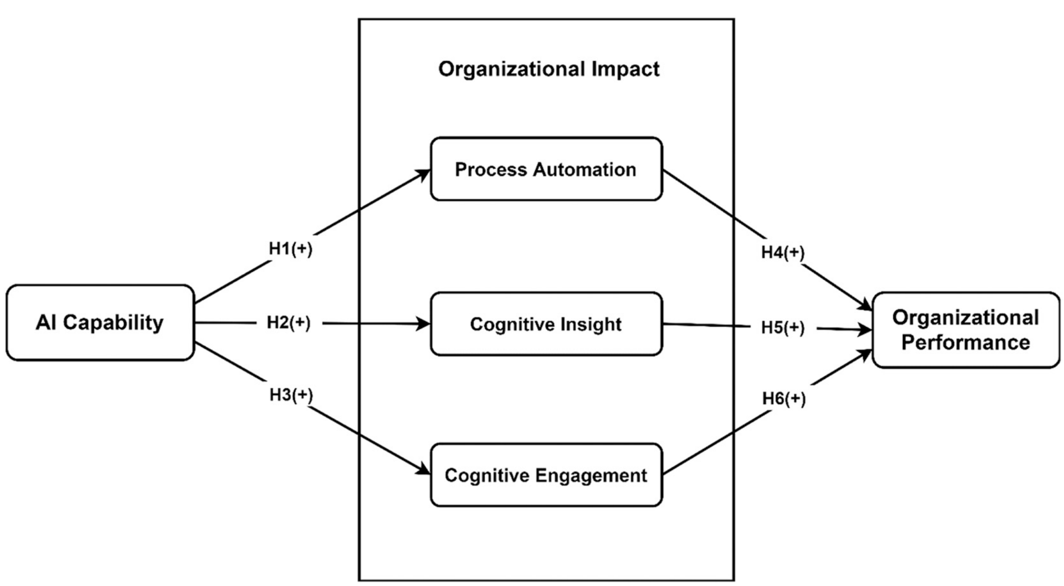

Fig. 1. Research Model and Hypotheses.

Apart from aiding in automating manual and repetitive processes, developing an AI capability also is expected to enhance the ability of public organizations to generate insights through data analysis. Through applications such as clustering, unsupervised machine learning, and classification, public organizations can uncover hidden insight that can aid decision-making (Singh, Dwivedi, Kahlon, Pathania, & Sawhney, 2020). The potential applications of such techniques are manifold, and include better forecasting and prediction for maintenance, extreme weather phenomena, predictive resource scheduling, and many more (Wirtz et al., 2019). For such applications, however, to be effective, it is important that public organizations have established appropriate data and technological resources, have technical and operational staff that understands how AI applications can be applied, and have put in place appropriate structures and processes to facilitate such collaboration (Sun & Medaglia, 2019). From the foregoing argument we hypothesize the following:

H2. AI capabilities will have a positive effect on cognitive insight.

In addition to the above two application areas of AI, there are many case examples in public organizations where AI has been used to enhance engagement with citizens and employees (Wirtz et al., 2019). Specifically, AI applications such virtual agents have been shown to increase the work performance of employees in public organizations by providing them with accurate and timely information when needed, and increasing overall efficiency and productivity (Bickmore, Rubin, & Simon, 2020). Apart from increased engagement with employees through, AI capabilities are argued to also make public organizations more attuned with needs of citizens (Androutsopoulou et al., 2019). Kankanhalli, Charalabidis, and Mellouli (2019a) suggest that the ability of public organizations to respond rapidly with digital technology change and innovate by means of AI, has the potential to achieve better citizen engagement by increasing collaboration among stakeholders in local communities. Doing so, nonetheless, requires a technical competence combined with a good overview of the requirements of citizens, and the capacity to rapidly deploy novel technological solutions to address demands and problems. We therefore hypothesize that:

H3. AI capabilities will have a positive effect on cognitive engagement.

Although an AI capability is argued to prompt changes in the three organizational activities described above, performance effects are suggested to be realized indirectly. This means that by enhancing process automation, cognitive insight, and cognitive engagement, public organizations will be more likely to realize performance gains. As such, organizational performance is dependent on how such applications are prioritize, as well as how timely and relevant they towards the activity they aim to contribute. We therefore develop the argumentation that organizational impacts of AI will lead to organizational performance improvements.

Automating manual and repetitive processes by means of AI has been argued to significantly reduce the time needed to complete processes, contribute to reduction of human errors, and enhance transparency of activities (Manyika et al., 2017). In the case of public organizations, such processes comprise a very large part of everyday tasks, whether they include handling applications, dealing with large amounts of documents, or entering and transferring data (Poister & Streib, 2001). Being able to handle such processes has been argued to impact the long-term viability and effectiveness of public sector organizations in terms of efficiency and management capacity. Furthermore, the capability to automate manual processes enables public organizations to free up personnel that can be used in more constructive tasks, which require human judgment, creativity, empathy, and problem solving (Wilson & Daugherty, 2019). From the above discussion we therefore hypothesize that:

H4. Process automation will have a positive effect on organizational performance.

Based on the proposed set of hypotheses, H1 and H4, we argue that an AI capability will have an indirect effect on organizational performance by enabling improvements in process automation. Therefore, we argue that:

Ha. AI capabilities will have a positive indirect effect on organizational performance, which will be mediated by a positive effect on process automation.

An additional challenge that most public organizations need to be able to handle with their limited resources is now to take informed actions and optimize their use of resources (Shareef et al., 2021). By providing actionable insight into vast quantities of data, public organizations can benefit by proactively taking action before situations worsen (e.g., predictive maintenance on public infrastructure), optimally making use of financial, physical, and human resources based on the ability to forecast future events, as well as take action based on information that was previously inaccessible (Brandt, Wagner, & Neumann, 2021; McBride, Aavik, Toots, Kalvet, & Krimmer, 2019). For instance, having the capacity to gain cognitive insight allows public organizations to be able to better identify and address the needs of citizen clusters that were previously overlooked or marginalized (van Ooijen, van Ubaldi, & Welby, 2019). It also facilitates a more detailed understanding of citizen service requirements and can be used to proactively support personalized information dissemination (e.g., notification of school registration deadlines to parents, reminder of important deadlines or applications etc.). Recent studies have also shown that such cognitive insight can have major performance effects in smart cities, and in cases of public administration where there are vast quantities of fast-paced data (Kankanhalli, Charalabidis, & Mellouli, 2019b). Based on the above we hypothesize that:

H5. Cognitive insight will have a positive effect on organizational performance.

Building on the hypotheses, H2 and H5, we suggest that an AI capability will have an indirect effect on organizational performance by enhancing the cognitive insights of organizations. Therefore, we argue that:

Hb. AI capabilities will have a positive indirect effect on organizational performance, which will be mediated by a positive effect on cognitive insight.

Being able to have closer interactions with citizens has long been argued to be a driver for innovation and improved service provision by public organizations (de Jong, Neulen, & Jansma, 2019). In turn, the enhanced engagement of citizens with public bodies has been found to increase perceptions of trust and satisfaction with public and governmental organizations (Simonofski, Snoeck, Vanderose, Crompvoets, & Habra, 2017). Furthermore, enhancing employees work tasks through the use of timely and relevant information has the potential to reduce work errors, increase efficiency, and reduce feelings of stress and work fatigue (Valle-Cruz, Alejandro Ruvalcaba-Gomez, Sandoval-Almazan, & Ignacio Criado, 2019). Such effects are argued to increase the overall service quality provided by public organizations, and to improve overall performance by providing closer and more engaged interactions with both citizens and employees. Recent empirical studies have documented such effects through the use of chatbots with citizens (Androutsopoulou et al., 2019), as well as intelligence agents for employees of government bodies (de Bruijn, Warnier, & Janssen, 2021; Janowski, Pardo, & Davies, 2012). We therefore hypothesize the following:

H6. Cognitive engagement will have a positive effect on organizational performance.

Grounded on the argumentation of hypotheses, H3 and H6, we propose that an AI capability will have an indirect effect on organizational performance by improving cognitive engagement realized through AI. Therefore, we argue that:

Hc. AI capabilities will have a positive indirect effect on organizational performance, which will be mediated by a positive effect on cognitive engagement.

4. Method

4.1. Survey administration and data

A survey-based method was employed to collect data from multiple municipalities as part of this study in three different European countries, Norway, Germany, and Finland. We opted for a quantitative survey-based study as it allows for confirmatory analysis, and allows the simultaneous inclusion of several factors (Pinsonneault & Kraemer, 1993). Furthermore, survey methods are also a good means to capture general tendencies and identify complex relationships between several key concepts in a study. While survey-based research is important in confirming formulated hypotheses, Straub, Boudrean, and Gefen (2004) argue that survey-based research is relevant in exploratory settings. As part of this research, we used constructs and corresponding items that were adopted or adapted from previously published studies. All constructs and respective items were measured on a 7-point Likert scale, which is a common practice in empirical research where there are no objective measures (Kumar, Stern, & Anderson, 1993).

Prior to launching the survey, we deployed it to a group of researchers with significant experience to verify that the content was clear and understood. Because data was collected from different European countries (i.e., Finland, Germany, and Norway), the survey was available in four languages (English, German, Norwegian, and Finish). During the pre-test, the group of participants noted some minor adjustments that required editing to be more comprehensible. The three European countries that we collected data from feature similarities with regards to their AI strategies and their AI progress. When comparing the three countries between them we did not find any significant differences regarding the constructs used in the study. We can attribute this finding to the fact that all three countries have very similar expenditure in public administration budgets as and particularly in terms of budgets directed towards digitalization (EC, 2021).

To investigate if our hypotheses are confirmed we collected data by means of an online questionnaire. Email invitations were sent out to key respondents in municipalities inviting them to participate through a link for an online questionnaire. The group of respondents that were targeted comprised primarily of chief digital officers and higher-level technology managers. A mailing list directory was developed for the municipalities of each country separately, and information about the best suited respondent was obtained through publicly available data. In cases where information on relevant respondents was not available on these websites, we sent a request to the general email address of each municipality asking for the contact details of respondents that were an appropriate match. After the initiation invitation, we sent out three reminders to increase response rates. The data collection processes begun in late October 2021 and was concluded in early Hune 2022. The final sample consisted of 197 responses of which 168 were complete and usable for further analysis.

From our sample of municipalities, there was a range in terms that were rather small in terms of population (under 1000 citizens), to those that were quite large (over 300,000 citizens). Most responses came from Norwegian municipalities that accounted for 62% of the sample, followed by Germany at 32%, and Finland at 6%. Response rates differed between the countries, with the highest being in Norway (32%), Germany (19%), and Finland (5%). The differences in response rates can be attributed to the fact that authors that contacted the municipalities had a higher degree of prior interaction with them in Norway compared to Germany and Finland. With regards to the position respondents held, we were able to attain data from personnel holding key positions related to IT, such as chief digital officers, IT directors, and IT managers. In addition, the majority of municipalities were well-staffed in their IT departments having on average >10 dedicated employees working on IT projects. Furthermore, a large portion of the sample had a significant number of employees in their IT departments (50+ employees). In terms of their use of AI, the largest proportion of companies had been using AI for approximately 2 years (38%) to 3 years (36%) (Table 1).

As the data collected for this study represented a snapshot in time and were perceptions of single respondents, we took several measures to reduce any potential bias. Specifically, we followed the guidelines of Podsakoff, MacKenzie, Lee, and Podsakoff (2003) and performed a number of tests to examine if there was cause for concern regarding common method bias. At a first stage, we conducted a Harmon one-factor tests on the five latent variables used in the study. The results of the analysis did not produce a unifactorial solution, with the maximum variance explained by any one factor being 31.5%. This result provided an indication that there is no major concern regarding common method bias. Furthermore, we followed the suggestions of Tenenhaus, Vinzi, Chatelin, and Lauro (2005) and looked at the goodness-of-fit indicator through PLS path modeling. Our outcomes show that the research model has a satisfactory goodness-of-fit as it surpasses the lower limit of 0.36 as suggested by Wetzels, Odekerken-Schröder, and van Oppen (2009). These outcomes confirm that common method biases are not an issue in our research model.

To further exclude the possibility of bias during our sampling, we performed a series of additional analyses. Specifically, the profile of municipalities that were included in this study sample was compared (e.g., size, country) with those for which no, or incomplete responses were received. By running a chi-square analysis, we found that there was no indication of response bias. Finally, we compared early with late respondents in terms of different sample demographic characteristics and documented no significant differences that would mean that our sample contains biased data. To check for internal validity, we followed an inclusive selection process by sending requests to all municipalities in each country and followed the exact same procedures for administration and treatment so as not to introduce any effects. To ensure that external validity criteria were met, we used a number of 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

Table 1
Descriptive statistics of the sample and respondents.

Factors	Sample (N = 168)	Proportion (%)
Country		
Norway	104	62%
Germany	53	32%
Finland	11	6%
Respondent's position		
Chief Digital Officer (CDO)	111	66%
IT director	37	22%
IT manager	17	10%
Operations manager	3	2%
Municipality size (Number of citizens)		
1000–9999	21	13%
10,000–24,999	30	18%
25,000–49,999	52	31%
50,000–99,9999	41	24%
100,000–299,999	20	12%
300,000 +	4	2%
Department size (Number of employees)		
1–9	21	13%
10–49	88	52%
–249	55	33%
+	4	2%
Length of AI use in municipality (Number of years)		
< 1 year	12	7%
year	19	11%
2 years	63	38%
years	61	36%
4 + years	13	8%

understanding of the notion (Kar, Rao, & Angelopoulos, 2020).

4.2. Measurements

The scales for the variables used in this study were primarily adapted or adopted from prior studies and have therefore been tested on their psychometric properties. All questions were 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.

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

Process automation (PA), cognitive insight (CI), and *cognitive engagement (CE)* were developed based on the study of Davenport and Ronanki (2018). The constructs were developed based on the definition provided by the authors and the detailed description of the changes in state of the three categories. Based on the definition, a pool of items was developed and through a series of activities with a group of seven experts they were refined and validated through the process described by MacKenzie, Podsakoff, and Podsakoff (2011). *Process automation* captures the extent to which AI has resulted in processes improvements in the focal organization. *Cognitive insight* measures the degree to which the use of AI has resulted in the ability to gain insight into citizen needs and uncover hidden knowledge. Cognitive engagement measures the level to which AI use has resulted in increased responsiveness and satisfaction of citizen requests and helped employees in answering job related queries.

Organizational performance (ORP) captured the degree to which the municipalities had perceived an increase of efficiency and overall performance in their related tasks. It was captured based on measurements of previous published work (Refs).

5. Analysis

To examine our hypothesized relationships and to confirm our model's validity and reliability, this study employed a partial least squares-based structural equation modeling (PLS-SEM) analysis. Specifically, we used the software package SmartPLS 3 as it allows for the analysis of both the measurement and structural models (Ringle, Wende, & Becker, 2015). PLS-SEM is deemed as suitable for this study as it enables the concurrent estimation of multiple hypotheses between one or more independent variables, and one or more dependent variables (Akter, Wamba, & Dewan, 2017; Hair Jr & Hult, 2016). Compared to other structural equation methods, PLS-SEM has the advantage of (i) flexibility regarding the assumptions on multivariate normality, (ii) allowing the researcher to use reflective and formative constructs, (iii) being able to compute complex models with smaller samples, (iv) facilitating the estimation of formative constructs, and (v) including functionality as a predictive tool for theory building (Nair, Demirbag, Mellahi, & Pillai, 2018).

Within the field of information systems (IS) research using PLS-SEM is common practice, 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) One of the reasons for using PLS-SEM in such settings is that it allows for a calculation of indirect and total effects. Doing so permits the simultaneous assessment of the relationships between multi-item constructs while reducing the overall error (Akter et al., 2017; Astrachan, Patel, & Wanzenried, 2014). Furthermore, the final sample of 168 responses exceeds 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, Ringle, & Sarstedt, 2011). Lastly, PLS-SEM is an appropriate method as this study is based on an exploratory approach rather than a theory confirmation.

5.1. Measurement model

Our suggested research model contains both reflective and formative constructs. Hence, we used different assessment criteria to evaluate each. In addition, we included additional analyses to validate the higher-order construct used in the study (i.e., AI capabilities). As a first step in assessing the measurement model we examined the statistical properties of first-order reflective latent constructs. For reflective constructs we examined their reliability, convergent validity, and discriminant validity. We gauged reliability at the construct and item levels. At the construct level, we examined the Composite Reliability (CR) and Cronbach Alpha (CA) values, ensuring that they were above the lower threshold of 0.70 (Nunnally, 1978). At the item level, we assessed construct-to-item loadings to confirm that all were above the lower limit of 0.70 on their respective construct (Appendix B). To confirm convergent validity, we used the Average Variance Extracted (AVE) values computed by SmartPLS and made sure that all exceeded the lower threshold of 0.50. We established discriminant validity by confirming that each indicator loading was higher than the cross-loadings with other constructs (Appendix B), and by running a Heterotrait–Monotrait ratio (HTMT) analysis (Henseler, Hubona, & Ray, 2016). The results from the HTMT ratio analysis indicated that all values were below 0.85 which confirms that validity has been established (Appendix C). The results are presented in Table 2, and suggest that the first-order reflective variables are valid to work with and are good indicators of their respective constructs.

Following the valuation of the formative constructs, we next proceeded to assess the formative constructs used in this study. Specifically, for first-order formative constructs (Table 3) we examined the weights and significance of items onto their corresponding constructs. Following the guidelines of Cenfetelli and Bassellier (2009), we opted to no remove any items as long as there is strong theoretical justification for their inclusion in the measurement model. Next, we examined 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).

At second stage, we proceeded to ensure that second order and third order formative constructs were valid following the same procedure. This included 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 outcomes of our structural model after running the PLS analysis are presented in Fig. 2. In the figure, we include the explained variance of endogenous variables (R^2), the standardized path coefficients (β), as well as the significance degrees of our hypothesized relationships. We gauge the outcomes by looking at the coefficient of determination (R^2) values, predictive relevance (Stone-Geisser Q^2), and the effect size of path coefficients. The significance of estimates (t-statistics) was obtained through the bootstrapping algorithm of SmartPLS in an analysis with 500 resamples. As illustrates in Fig. 2, five out of the six hypotheses were found to be statistically significant and positive, while one was found to negative and marginally significant. Specifically, we found that that an AI capability has a positive and significant effect on all three organizational impact outcomes, process automation ($\beta = 0.503$, $t = 6.259$, $p < 0.001$), cognitive insight ($\beta = 0.538$, $t = 7.127$, $p < 0.001$), and cognitive engagement ($\beta = 0.492$, $t = 6.119$, $p < 0.001$). Process automation in turn has a positive and significant effect on organizational performance ($\beta = 0.297$, $t = 5.333$, $p < 0.001$), as does cognitive insight ($\beta = 0.430$ $t = 6.475$, $p < 0.001$). Surprisingly, we find that cognitive

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
1	Data	n/a											
2	Technology	0.80	n/a										
3	Basic Resources	0.78	0.81	n/a									
4	Technical Skills	0.61	0.79	0.63	0.88								
5	Business skills	0.54	0.77	0.66	0.69	0.85							
6	Inter-departmental Coordination	0.42	0.29	0.24	0.24	0.48	0.88						
7	Organizational Change Capacity	0.29	0.29	0.24	0.20	0.45	0.64	0.81					
8	Risk Proclivity	0.54	0.66	0.52	0.55	0.53	0.58	0.54	0.91				
9	Process Automation	0.34	0.42	0.28	0.35	0.37	0.42	0.46	0.47	0.84			
10	Cognitive Insight	0.30	0.44	0.41	0.37	0.40	0.41	0.42	0.48	0.52	0.93		
11	Cognitive Engagement	0.29	0.39	0.41	0.43	0.38	0.43	0.49	0.50	0.56	0.56	0.94	
12	Organizational Performance	0.34	0.36	0.35	0.25	0.42	0.47	0.52	0.57	0.54	0.61	0.59	0.84
	Mean	2.95	3.38	2.58	2.55	3.16	4.72	4.76	3.67	3.73	3.12	3.44	4.53
	Standard Deviation	1.41	1.80	1.40	1.52	1.60	1.25	1.23	1.52	1.45	1.52	1.43	1.72
	AVE	n/a	n/a	n/a	0.78	0.73	0.78	0.65	0.82	0.71	0.85	0.88	0.71
	Cronbach's Alpha	n/a	n/a	n/a	0.96	0.96	0.95	0.89	0.89	0.95	0.95	0.96	0.89
	Composite Reliability	n/a	n/a	n/a	0.96	0.96	0.96	0.92	0.93	0.96	0.97	0.97	0.92

Table 3
First-order formative construct validation.

Construct	Measures	Weight	Significance	VIF
Data	DT1	0.099	$p < 0.05$	1.998
	DT2	0.217	$p < 0.001$	2.951
	DT3	0.114	$p < 0.05$	2.055
	DT4	0.511	$p < 0.001$	2.773
	DT5	0.277	$p < 0.001$	2.432
	DT6	0.203	$p < 0.001$	2.556
Technology	TC1	0.479	$p < 0.001$	2.333
	TC2	0.143	$p < 0.001$	3.003
	TC3	0.257	$p < 0.001$	2.533
	TC4	0.171	$p < 0.001$	1.472
	TC5	0.317	$p < 0.001$	1.568
	TC6	0.179	$p < 0.001$	2.536
	TC7	0.222	$p < 0.001$	2.486
Basic Resources	BR1	0.237	$p < 0.001$	3.011
	BR2	0.446	$p < 0.001$	2.586
	BR3	0.233	$p < 0.001$	2.698

Table 4
Higher-order formative construct validation.

Construct	Measures	Weight	Significance	VIF
Tangible	Data	0.365	$p < 0.001$	2.644
	Technology	0.498	$p < 0.001$	3.056
	Basic Resources	0.216	$p < 0.001$	2.892
Human	Managerial Skills	0.513	$p < 0.001$	2.187
	Technical Skills	0.514	$p < 0.001$	2.201
Intangible	Inter-Departmental Coordination	0.457	$p < 0.001$	2.253
	Organizational Change Capacity	0.355	$p < 0.001$	2.575
	Risk Proclivity	0.267	$p < 0.001$	1.683
BDAC	Tangible	0.374	$p < 0.001$	3.002
	Human	0.496	$p < 0.001$	3.107
	Intangible	0.252	$p < 0.001$	3.132

engagement has a marginally-significant negative effect on organizational performance ($\beta = -0.177$, $t = 1.992$, $p < 0.05$).

The structural model explains 61.3% of variance for process automation ($R^2 = 0.613$), 65.6% for cognitive insight ($R^2 = 0.656$), and 52.1% for cognitive engagement ($R^2 = 0.521$). Finally, the model explains 41.3% of variance for organizational performance ($R^2 = 0.405$). In addition, to further validate our outcomes 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 all values are above the thresholds of either 0.15 or 0.35. These outcomes help us conclude that the exogenous variables have moderate to high effect sizes. To examine for the effect of confounding, we also assessed the impact that control variables have on the organizational performance of municipalities. As depicted in Fig. 2, the control variables we included had a non-significant effect.

5.3. Test for mediation

To examine if the impact of AI capabilities on organizational performance is direct or is mediated by the three forms of organizational impact, a bootstrapping approach is employed, a nonparametric resampling procedure that imposes no assumptions on normality of sampling distribution (Hayes, 2017). Based on the guidelines of Hair Jr and Hult (2016), we first confirm that the mediated paths (AIC → PA → ORP, AIC → CI → ORP and AIC → CE → ORP) are significant. By then, including the direct path (AIC → ORP) in the model, we find that it retains part of its significance ($\beta = 0.179$, $t = 1.999$, $p < 0.01$) which is an indication of partial mediation. To examine the mediation hypotheses, we used the parameter estimates from the bootstrapping procedure in PLS, based on a resampling of 5000 subsamples, and calculated the standard error of each mediation effect. We then calculated the t-statistic for each mediation path by dividing the effect of the indirect path (i.e., the product of each indirect path), by the standard error of mediation effects. This approach of assessing the significance of indirect paths provides the advantage of not imposing any distributional assumptions of the indirect effects. In addition, it allows for the calculation of the entire indirect effect simultaneously in the presence of multiple mediating effects rather than isolating part of the structural model. The results indicate that the mediating paths largely, but not completely, explain the effect that AI capabilities have on organizational performance.

5.4. Predictive validity

Apart from assessing R^2 values, we also examined Q^2 predictive relevance of exogenous variables (Woodside, 2013). The predictive relevance score measures how well values are replicated by the model and its parameter estimates using sample re-use (Chin, 1998). This method is combines cross-validation and function fitting and calculates the predictive relevance of each variable by omitting inner model associations and computing changes in the criterion estimates (q^2) (Hair, Sarstedt, Ringle, & Mena, 2012). Values of Q^2 that are >0 are an indication that the structural model has strong predictive relevance. Contrarily, values below 0 are a sign of low predictive relevance (Hair Jr, Hult, Ringle, & Sarstedt, 2016). Our results indicate that the dependent variables all have a satisfactory predictive relevance. Lastly, q^2 values are above the value of 0.35, indicating that the effect size of predictive relevance is high.

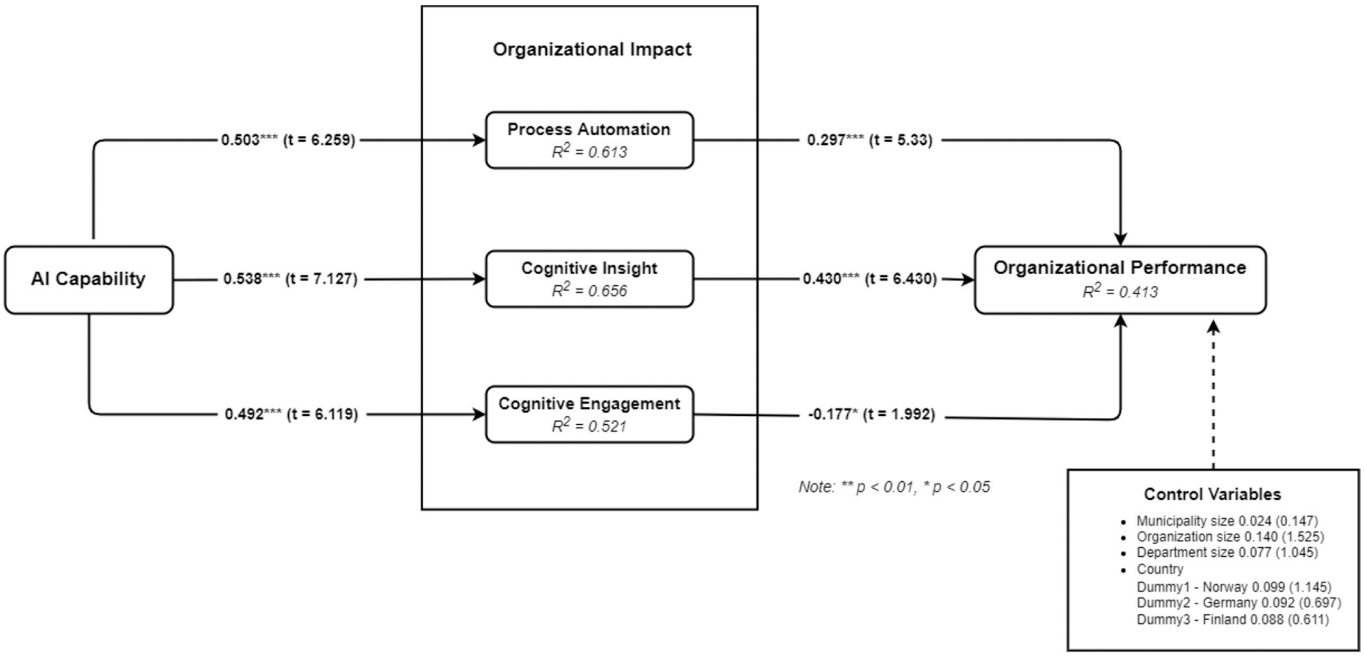

Fig. 2. Results of the PLS-PM estimation (β*** significant $p < 0.01$, β** significant $p < 0.05$, β* significant $p < 0.1$, n.s. = non-significant).

6. Discussion

In this study we have sought to understand the role of AI capabilities in the organizational impact of AI. As public sector organizations such as municipalities are starting to use AI technologies, understanding how AI capabilities can impact the use of AI and how the use of AI tools to automate processes, gain cognitive insight and engage stakeholders can result in improved organizational performance. We selected organizational performance as the focus of our interest as it is a good measure to evaluate whether the transformations in AI utilization with AI capability can result in the improvements in organizational performance, which AI utilizations typically aspire (Wirtz et al., 2019). The mere consideration of the role of AI capabilities would not have provided an adequate understanding of whether the organizational change in AI utilization will result in the desired benefits.

Following a survey-based quantitative study we collected responses from 168 municipalities located in Norway, Germany, and Finland. Using PLS-SEM to analyze data, we examine our proposed research model and find that following our hypotheses, five out of six hypotheses are confirmed. Specifically, we find that an AI capability has a positive and significant effect on the three types of organizational impacts: process automation, cognitive insight, and cognitive engagement. This finding confirms our hypotheses that an AI capability is a necessary organizational capacity in order to be able to effectively leverage AI investments. In turn, the effects of an AI capability will indirectly influence organizational performance. In alignment with our theorizing, we find that process automation and cognitive insight positively and significantly affect organizational performance. Contrarily, cognitive engagement exerts a negative, yet less significant effect on organizational performance.

6.1. Implications for research

This study contributes to research on AI utilization in the public sector by linking AI capabilities to organizational performance and by demonstrating that while AI capabilities have a positive impact on the utilization of AI technologies this capability does not necessarily always result in improvements in organizational performance. Specifically, our results confirm previous findings of studies such as Mikalef and Gupta (2021) that AI capabilities have a positive impact in generating organizational change through process automation, cognitive insights, and cognitive engagement. However, this organizational change does not necessarily always lead to improvements in organizational performance. This discovery as well is in line with previous findings from the private sector where research has indicated that the impact of AI in organizational performance is still limited (Brynjolfsson, Rock, & Syverson, 2017).

Our results also show that these different applications of AI have very different effects on performance, where the cognitive insights support organizational performance, process automation creates some improvements in the organizational performance and cognitive engagement affects the performance negatively. These differences can be at least partly explained by the fact that process automation creates value within existing processes whereas cognitive insight can create new value paths, which can be easier to identify by respondents of the survey, who hold higher-level managerial positions. The variation between these three AI applications can also be traced to the current tendency of public sector organizations to focus on small-scale AI implementations due to which their impact on organizational performance can be limited (Thierer, O'Sullivan, & Russell, 2018; Wirtz et al., 2019) or on the other hand difficult to detect. Nonetheless, our study indicates that when organizations hold adequate AI capabilities, they also can generate improvements in organizational performance through the utilization of AI technologies, at least in the case of cognitive insight and process automatization.

However, we find that there is a negative correlation between cognitive engagement and organizational performance. For this, multiple explanations can be identified. First, the negative impact of cognitive engagement on performance can be a result of a mismatch between expectations and reality (Brynjolfsson et al., 2017; Hameed, Tan, Thomsen, & Duan, 2016). For example, introducing customer chatbots can create false hope in instantaneous efficiency improvements in managing customer contacts, even though introducing these new tools can initially require significant efforts in improving the system (Davenport & Ronanki, 2018) as well as in gaining societal acceptance for the new tool (Wirtz et al., 2019). Second, the concerns related to AI, for example, the negative impacts it can have on the workforce can initially result in resistance in using these new tools (Fast & Horvitz, 2017; Mehr, 2017), which can result in a situation where an organization uses resources in implementing and upkeeping AI tools that are not used and consequently create a negative effect on organizational performance. Overall, AI applications such as chatbots require both internal and external commitment (Aoki, 2020), the building of which can initially require more resources than what the benefit of these applications can eventually be. This supports the observation that although the current AI research has largely focused on technical aspects, other organizational factors need to be considered as well (Ågerfalk, 2020).

The negative effects of cognitive engagement on organizational performance also open up some interesting new avenues for further research. Specifically, for all three types of organizational impacts, it is important to understand how exactly the affordances that are enabled by AI lead to performance gains or losses. It is important, therefore, to trace the mechanisms through which value is added to public organizations and how to optimize it. In our results, perhaps one potential explanation of the outcome relating to cognitive engagement and the negative effects on organizational performance could be due to the low maturity of such solutions. For instance, chatbots are at an early stage of deployment and often do not offer the necessary assistance to citizens. This entails those human personnel needs to handle such cases, and in the same time work with developers of AI solutions in order to improve such AI applications. This poses a large burden on public organizations that need to invest time and effort before AI applications can be more functional.

6.2. Implications for practice

Our study also points to some important practical implications that are of relevance for stakeholders within public organizations. First, for IT and technology managers in municipalities our findings show that they need to develop an organization-wide readiness perspective when deploying AI applications. This poses a challenge to them as they need to make clear to managers of operational departments that AI applications require a holistic effort from the entire organization in order to be developed and in turn, to be of value. Simply seeing AI as a technical task and focusing on technology adoption through infrastructure investments and pools of data is unlikely to contribute towards value realization in AI-driven deployments. In addition, our findings show that human factors are equally as important in deriving value from AI applications. Being able to develop technical and business skills around AI is crucial. Therefore, managers need to put into place incentives and schemes to train personnel with the new developments in the fields of AI. Last, but not least it is important that public organizations embrace a more risk-oriented culture where they initiative technology projects of high-risk and high-gain. This requires that the entire organization is aligned and sees AI as a strategic tool.

In terms of effects of AI capabilities, our findings demonstrate to managers that applications of AI can have very different effects depending on what type of improvement they are seeking to prompt. As applications of AI are very diverse in their nature, it is impossible to realize value in many different operational activities. This poses both a challenge and a great opportunity for managers as they can identify weaknesses or points that need to be improved in their focal organizations and deploy appropriate AI solutions to improve them. For instance, if municipalities are understaffed and are dealing with large amounts of application processes, automating manual and repetitive processes is a good way to free up some human capital. Within this sub-domain there are also a plethora of tools that can be used depending on if the automation of processes requires merely a rule-based system or even a sort of machine vision. The findings of our analysis also provide empirical support to the claim that by introducing AI in such operations, managers can expect to realize identifiable impacts of organizational performance.

Extending on the previous point, our findings also highlight that the different types of improvement changes wrought by AI capabilities will require from IT managers to adopt different types of technologies. As mentioned in our study, AI comprises a diverse set of technologies and techniques. This obviously has some important repercussions regarding the type of technical infrastructure that needs to be invested in, as well as the types of skills key employees will need to possess. Therefore, it is important that municipalities and public bodies in general begin with a top-down approach, where they define the objectives they want to achieve, determine what organizational mechanisms need to be prompted to achieve such goals, and then invest in the appropriate AI resources to achieve this goal. The AI capability notion therefore acts as a means of identifying all the relevant resources that need to be considered when doing so in order to ensure that the set outcomes are attained.

6.3. Limitations and future research

Although our study contributes to the current body of research on AI and organizational value, it is not without limitations. First, the sample of municipalities that we used in this study was only from three countries in northern Europe. Therefore, it may not be representative of the situation in other countries where other barriers may limit organizational value. The three countries we gathered data from are quite homogenous in terms of availability of resources and socio-economic conditions. Second, while we managed to collect data from a large number of municipalities to document effects, such effects represent only a snapshot in time. Therefore, there is a limitation that we cannot how AI capabilities over time result in organizational changes. There may be additional internal and external contingencies that are likely to emerge as important forces in the generation of value. Future studies can therefore focus on longitudinal studies to identify the evolution and mechanisms of effects of AI capabilities. Third, our analysis may differentiate between three types of AI effects, but it is not going into much depth regarding how they are realized. For instance, municipalities between them may have very different ways of attaining process automation and it may be pertinent to different activities. Hence, an interesting future direction would be to complement this work with more case studies that examine the finer details of how such organizational impacts are realized. Fourth, while we have employed several controls and detailed instructions towards respondents in the survey, the effects of performance are based on subjective measures. Hence, they reflect perceptions of performance which may entail bias, as they were from a single respondent. As AI applications in municipalities become increasingly more common, it is interesting to measure their effects on objective performance metrics. An alternative approach would be also to use a paired-responses survey method which could potentially reduce possible bias in answering.

CRediT authorship contribution statement

Patrick Mikalef: Conceptualization, Formal analysis, Writing – original draft, Writing – review & editing. **Kristina Lemmer:** Data curation, Investigation, Methodology, Writing – original draft. **Cindy Schaefer:** Data curation, Investigation, Methodology, Writing – original draft. **Maija Ylinen:** Data curation, Investigation, Methodology, Writing – original draft. **Siw Olsen Fjørtoft:** Project administration, Resources. **Hans Yngvar Torvatn:** Project administration, Resources. **Manjul Gupta:** Conceptualization, Supervision. **Bjoern Niehaves:** Resources, Supervision.

Declaration of Competing Interest

There are not potential conflicts of interest in this study that we need to disclose. The study did not receive funding or was part of any other project.

Appendix A. Survey instrument

Measure	Item
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
	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
Organizational Impact	
	PA1. The use of AI has enabled us to automate back office administrative tasks
	PA2.The use of AI has allowed us to automate financial activities
– Process automation	PA3. The use of AI has helped us automate structured tasks (e.g. transferring of data, updating records)
	PA4. The use of AI has helped us automate complex human processes of our employees
	PA5. The use of AI has enabled us to free up employees in tasks that are now automated
	PA6. The use of AI has optimized our information systems itself (e.g. optimizing processes, machine learning)
	CI1. The use of AI has allowed us to gain insight about our citizens preferences
– Cognitive Insight	CI2. The use of AI has enabled us to develop a better understanding of our citizens needs
	CI3. The use of AI has allowed us to generate insight in key business activities that we previously did not have access to

(*continued on next page*)

(*continued*)

Measure	Item
	CI4. The use of AI has allowed us to uncover knowledge that we previously were unaware of
	CI5. The use of AI has allowed us to optimize business operations by providing key insight
– Cognitive Engagement	CE1. The use of AI has enhanced our responsiveness to citizen service requests. CE2. The use of AI has helped us satisfy citizen needs. CE3. The use of AI has enabled us to increase engagement with citizens. CE4. The use of AI has allowed our employees to be more productive. CE5. The use of AI has helped our employees in answering their different job-related queries (e.g. voice-assistants, intelligent agents)
Organizational Performance	*Compared with how your organization was performing 1 year ago, please indicate how much you agree or disagree with the following statements*
	OP1. We have been able to reduce operating costs.
	OP2. We have been able to increase efficiency.
	OP3. We have been able to generate more knowledge.
	OP4. We have been able to increase the quality of our services.
	OP5. We have been able to increase the level of innovation output.
	OP6. We have been able to improve the speed to which we respond to requests.
	OP7. We have been able to serve more citizens.
	OP8. We have been able to increase agility in changing the way we do things.
	OP9. We have been able to reduce bottlenecks.
	OP10. We have been able to improve the speed to which we develop new solutions for our citizens.
	OP11. We have been able to improve the reliability of our IT systems.

Appendix B. Cross loadings

	D	T	BR	TS	BS	IC	OC	RP	PA	CI	CE	OP
D1	**0.70**	0.50	0.23	0.43	0.44	0.48	0.47	0.50	0.34	0.46	0.23	0.61
D2	**0.85**	0.60	0.50	0.44	0.27	0.21	−0.01	0.32	0.45	0.44	0.33	0.38
D3	**0.89**	0.53	0.49	0.44	0.33	0.45	0.26	0.51	0.45	0.50	0.30	0.43
D4	**0.83**	0.75	0.71	0.69	0.70	0.45	0.31	0.65	0.57	0.62	0.50	0.58
D5	**0.82**	0.62	0.59	0.54	0.38	0.32	0.12	0.34	0.49	0.63	0.54	0.55
D6	**0.81**	0.47	0.70	0.39	0.42	0.34	0.32	0.39	0.51	0.41	0.62	0.40
T1	0.68	**0.78**	0.75	0.69	0.71	0.31	0.31	0.52	0.71	0.74	0.62	0.52
T2	0.53	**0.79**	0.48	0.60	0.65	0.28	0.31	0.56	0.53	0.60	0.51	0.56
T3	0.48	**0.71**	0.58	0.51	0.64	0.08	0.18	0.55	0.53	0.39	0.52	0.53
T4	0.51	**0.81**	0.47	0.82	0.60	0.15	0.03	0.46	0.69	0.76	0.53	0.49
T5	0.59	**0.83**	0.52	0.86	0.64	0.20	0.01	0.61	0.65	0.82	0.55	0.54
T6	0.42	**0.70**	0.55	0.61	0.45	0.02	0.08	0.40	0.56	0.57	0.53	0.37
T7	0.60	**0.78**	0.66	0.82	0.65	0.25	0.15	0.50	0.72	0.81	0.72	0.58
BR1	0.63	0.72	**0.90**	0.59	0.65	0.16	0.16	0.49	0.64	0.50	0.61	0.31
BR2	0.55	0.64	**0.94**	0.64	0.51	−0.01	0.09	0.32	0.65	0.58	0.75	0.35
BR3	0.70	0.74	**0.98**	0.70	0.61	0.13	0.17	0.46	0.74	0.68	0.78	0.45
TS1	0.35	0.66	0.39	**0.80**	0.52	0.17	0.12	0.35	0.51	0.75	0.57	0.33
TS2	0.42	0.77	0.64	**0.79**	0.63	0.04	0.01	0.37	0.63	0.64	0.75	0.34
TS3	0.59	0.86	0.64	**0.97**	0.66	0.18	0.01	0.58	0.75	0.89	0.66	0.51
TS4	0.48	0.77	0.58	**0.93**	0.55	0.11	−0.05	0.43	0.68	0.82	0.64	0.34
TS5	0.72	0.90	0.75	**0.95**	0.71	0.20	0.10	0.64	0.78	0.89	0.67	0.61
TS6	0.63	0.80	0.76	**0.82**	0.68	0.21	0.17	0.55	0.84	0.74	0.74	0.57
TS7	0.53	0.79	0.53	**0.86**	0.58	0.19	0.21	0.52	0.73	0.87	0.56	0.56
TS8	0.51	0.84	0.51	**0.91**	0.69	0.13	0.15	0.61	0.61	0.84	0.50	0.56
BS1	0.43	0.58	0.27	0.48	**0.82**	0.64	0.56	0.79	0.27	0.47	0.19	0.67
BS2	0.37	0.58	0.40	0.44	**0.84**	0.63	0.63	0.70	0.37	0.48	0.39	0.71
BS3	0.28	0.53	0.41	0.47	**0.82**	0.35	0.48	0.77	0.38	0.36	0.29	0.58
BS4	0.43	0.73	0.58	0.64	**0.89**	0.27	0.36	0.65	0.50	0.60	0.68	0.61
BS5	0.51	0.64	0.56	0.54	**0.89**	0.53	0.64	0.78	0.49	0.49	0.44	0.74
BS6	0.46	0.71	0.56	0.56	**0.86**	0.39	0.49	0.65	0.57	0.52	0.59	0.66
BS7	0.46	0.77	0.62	0.70	**0.92**	0.47	0.41	0.64	0.65	0.65	0.65	0.57
BS8	0.53	0.81	0.75	0.74	**0.86**	0.32	0.26	0.58	0.71	0.69	0.79	0.50
BS9	0.53	0.80	0.59	0.83	**0.78**	0.40	0.33	0.65	0.71	0.80	0.66	0.51
IC1	0.44	0.32	0.13	0.22	0.47	**0.89**	0.66	0.42	0.32	0.35	0.27	0.53
IC2	0.46	0.19	0.06	0.12	0.43	**0.93**	0.69	0.48	0.07	0.21	−0.05	0.41
IC3	0.48	0.19	0.16	0.12	0.48	**0.95**	0.72	0.49	0.20	0.25	0.18	0.45
IC4	0.43	0.32	0.26	0.32	0.55	**0.85**	0.72	0.52	0.31	0.41	0.23	0.56
IC5	0.35	0.11	0.00	0.10	0.39	**0.85**	0.65	0.62	0.07	0.13	−0.05	0.37
IC6	0.39	0.26	0.06	0.18	0.51	**0.92**	0.66	0.46	0.14	0.21	0.09	0.41
IC7	0.20	0.12	−0.06	0.00	0.29	**0.75**	0.49	0.28	0.07	−0.02	−0.04	0.20
OC1	0.28	0.06	0.06	0.00	0.26	0.71	**0.73**	0.30	0.11	0.05	0.07	0.38
OC2	0.18	0.06	0.09	0.09	0.31	0.52	**0.79**	0.37	0.10	0.20	0.11	0.47
OC3	0.14	0.18	0.19	0.10	0.42	0.51	**0.82**	0.34	0.04	0.05	0.18	0.35
OC4	0.09	−0.10	−0.01	−0.20	0.12	0.45	**0.76**	0.28	−0.05	−0.17	−0.12	0.41
OC5	0.25	0.33	0.20	0.22	0.60	0.44	**0.72**	0.60	0.12	0.27	0.13	0.61
OC6	0.35	0.34	0.17	0.20	0.68	0.82	**0.91**	0.68	0.22	0.29	0.18	0.64
RP1	0.49	0.66	0.43	0.60	0.74	0.48	0.32	**0.85**	0.60	0.60	0.47	0.55
RP2	0.59	0.66	0.55	0.55	0.78	0.48	0.50	**0.94**	0.55	0.54	0.43	0.65
RP3	0.42	0.51	0.27	0.45	0.66	0.50	0.66	**0.92**	0.42	0.45	0.19	0.79

(*continued on next page*)

(*continued*)

	D	T	BR	TS	BS	IC	OC	RP	PA	CI	CE	OP
PA1	0.56	0.71	0.61	0.71	0.58	0.29	0.21	0.53	**0.91**	0.74	0.77	0.57
PA2	0.51	0.68	0.70	0.63	0.56	0.17	0.18	0.64	**0.89**	0.62	0.57	0.48
PA3	0.60	0.77	0.70	0.75	0.58	0.21	0.12	0.57	**0.94**	0.81	0.71	0.57
PA4	0.42	0.71	0.58	0.74	0.52	0.08	0.01	0.57	**0.84**	0.71	0.62	0.41
PA5	0.50	0.71	0.67	0.63	0.49	0.13	0.11	0.34	**0.93**	0.70	0.82	0.46
PA6	0.54	0.82	0.64	0.78	0.60	0.13	0.05	0.42	**0.88**	0.81	0.79	0.54
CI1	0.47	0.78	0.51	0.86	0.55	0.12	0.01	0.48	0.75	**0.92**	0.72	0.52
CI2	0.43	0.77	0.52	0.85	0.57	0.13	0.06	0.43	0.67	**0.92**	0.71	0.49
CI3	0.67	0.85	0.59	0.86	0.63	0.30	0.20	0.60	0.82	**0.95**	0.69	0.63
CI4	0.70	0.85	0.60	0.87	0.66	0.37	0.21	0.62	0.79	**0.95**	0.70	0.58
CI5	0.63	0.86	0.68	0.86	0.70	0.27	0.25	0.57	0.78	**0.95**	0.72	0.65
CE1	0.52	0.68	0.78	0.66	0.50	0.04	0.00	0.23	0.75	0.63	**0.94**	0.26
CE2	0.47	0.72	0.75	0.69	0.68	0.10	0.23	0.46	0.68	0.73	**0.92**	0.44
CE3	0.46	0.65	0.69	0.69	0.52	0.09	0.10	0.36	0.73	0.79	**0.92**	0.40
CE4	0.49	0.69	0.60	0.66	0.61	0.20	0.21	0.43	0.79	0.69	**0.91**	0.49
CE5	0.47	0.68	0.70	0.61	0.56	0.03	−0.01	0.29	0.72	0.63	**0.94**	0.38
OP1	0.49	0.53	0.33	0.47	0.75	0.46	0.64	0.73	0.38	0.48	0.30	**0.86**
OP2	0.57	0.56	0.40	0.45	0.48	0.31	0.33	0.46	0.62	0.51	0.61	**0.76**
OP3	0.37	0.49	0.33	0.34	0.41	0.17	0.44	0.22	0.43	0.39	0.44	**0.74**
OP4	0.54	0.60	0.35	0.49	0.72	0.52	0.64	0.78	0.46	0.55	0.32	**0.94**
OP5	0.51	0.61	0.26	0.51	0.61	0.48	0.52	0.79	0.48	0.61	0.22	**0.88**
OP6	0.31	0.63	0.30	0.20	0.60	0.28	0.29	0.72	0.63	0.30	0.20	**0.81**
OP7	0.22	0.66	0.37	0.21	0.62	0.39	0.73	0.38	0.48	0.22	0.43	**0.79**
OP8	0.35	0.30	0.27	0.25	0.57	0.58	0.48	066	0.39	0.36	0.29	**0.77**
OP9	0.50	0.60	0.47	0.55	0.68	0.13	0.23	0.34	0.70	0.61	0.56	**0.82**
OP10	0.55	0.54	0.43	0.65	0.52	0.09	0.10	0.10	0.23	0.46	0.52	**0.83**
OP11	0.20	0.21	0.43	0.49	0.25	0.69	0.68	0.10	0.23	0.53	0.30	**0.79**

Appendix C. Heterotrait-Monotrait ratio (HTMT)

	Construct	1	2	3	4	5	6	7	8	9
1	Technical Skills									
2	Business skills	0.534								
3	Inter-departmental Coordination	0.354	0.476							
4	Organizational Change Capacity	0.512	0.489	0.499						
5	Risk Proclivity	0.423	0.544	0.654	0.654					
6	Process Automation	0.659	0.170	0.277	0.489	0.407				
7	Cognitive Insight	0.662	0.194	0.254	0.350	0.437	0.354			
8	Cognitive Engagement	0.622	0.235	0.277	0.489	0.407	0.400	0.456		
9	Organizational Performance	0.476	0.466	0.257	0.357	0.477	0.378	0.368	0.546	

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Patrick Mikalef is an Associate Professor in Data Science and Information Systems at the Department of Computer Science. In the past, he has been a Marie Skłodowska-Curie post-doctoral research fellow working on the research project “Competitive Advantage for the Data-driven Enterprise” (CADENT). He received his BSc in Informatics from the Ionian University, his MSc in Business Informatics for Utrecht University, and his PhD in IT Strategy from the Ionian University. His research interests focus the on strategic use of information systems and IT-business value in turbulent environments. He has published work in international conferences and peer-reviewed journals including the European Journal of Information Systems, Journal of Business Research, British Journal of Management, Information and Management, and the European Journal of Operational Research.

Kristina Lemmer has been a research assistant at the Chair of Information Systems since 2016. She studied Business Administration (B. Sc.) And Controlling u0026 Risk Management (M. Sc.) At the University of Siegen.

Cindy Schaefer has been a research assistant at the Chair of Information Systems since the beginning of 2020. She studied industrial engineering specializing in electrical energy technology (B.Sc. and M.Sc.) at RWTH Aachen University.

Maija Ylinen is a doctoral researcher at the university of Tampere I the industrial management department.

Siw Olsen Fjørtoft Research scientist at SINTEF Digital, Trondheim, Norway. I have previously worked as a teacher and as a project manager for ICT in schools.

Hans Yngvar Torvatn is a research manager in SINTEF Digital in the department of technology management.

Manjul Gupta studies the role of national culture and organizational culture in a variety of technology-driven phenomena, such as the sharing economy, bitcoin adoption, big data, and social networks. His research has appeared in several leading journals including Management Information Systems Quarterly (MISQ), Production and Operations Management journal, Health Affairs, Information Management, and the Journal of Business Research. Dr. Gupta consults organizations on how to assess national cultural nuances for launching products/services in international markets and helps organizations in evaluating their existing cultures and implementing changes according to their vision.

Bjoern Niehaves stands for the topic of digital innovations and their importance for the entrepreneurial value creation and working world of today and tomorrow. After intermediate stops and others in Harvard (USA), Waseda University (Japan), London School of Economics (UK), Copenhagen Business School (DK) and Hertie School of Governance (DE), he is now the Chair of Information Systems and Director of the Research College (FoKoS) at the University of Siegen. In addition to his research, Professor Niehaves is a keynote speaker and consultant for leading companies, public administrations and international organizations. Many of his >300 publications have been awarded research and innovation prizes.