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Artificial intelligence in public services: When and why citizens accept its usage

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ABSTRACT

Interest in implementing artificial intelligence (AI)–based software in the public sector is growing. First implementations and research in individual public services have already been carried out; however, a better understanding of citizens' acceptance of this technology is missing in the public sector, as insights from the private sector cannot be transferred directly. For this purpose, we conduct policy-capturing experiments to analyze AI's acceptance in six representative scenarios. Based on behavioral reasoning theory, we gather evidence from 329 participants. The results show that AI solutions in general public services are preferred over those provided by humans, but specific services are still a human domain. Further analyses show that the major drivers toward acceptance are the reasons against AI. The results contribute to understanding of when and why AI is accepted in public services. Public administration can use the results to identify AI-based software to invest in and communicate their usage to perceive such investments' high acceptance rates.

1. Introduction

Interest in the potential of artificial intelligence (AI) is not only evident in the private sector but also growing rapidly in the public sector (e.g. Lindgren, Madsen, Hofmann, & Melin, 2019; Rosemann, Becker, & Chasin, 2020). The introduction of AI in organizations promises greater efficiency and higher-quality services (Sun & Medaglia, 2019). However, although there is already much research on AI in general, little attention has been paid to AI in the public sector (Sun & Medaglia, 2019). This is an important gap, as knowledge gained in the private sector cannot be fully transferred to the public because of citizens' perceptions of services (Radnor & Osborne, 2013; Schaefer et al., 2021). The public sector has goals other than maximizing value generation for paying customers (Kowalkiewicz & Dootson, 2019; Rosemann et al., 2020). Moreover, a multitude of services offered by the public sector affect many citizens, as they are provided in general without specific demand (e.g., traffic lights) (Walsh, 1991). Hence, public services can be divided into general (generally provided) and specific (individually requested) services (Halaris, Magoutas, Papadomichelaki, & Mentzas, 2007).

Nevertheless, public services have great potential for digital development (Kowalkiewicz & Dootson, 2019; Misuraca, van Noordt, & Boukli, 2020; Rosemann et al., 2020; Thierer, Castillo O'Sullivan, & Russell, 2017). eGovernment is the name applied to the digitization of the public sector (Wang & Liao, 2008). The use of information and communication technology (non-AI-based software) and its impact in the public sector have been widely studied (e.g. Alruwaie, El-Haddadeh, & Weerakkody, 2020; de Róiste, 2013; Esteves & Joseph, 2008; Wang & Liao, 2008).

A review of the literature by de Sousa, de Melo, Bermejo, Farias, and Gomes (2019) found growing interest in the use of AI applications in the public sector, with a particular focus on general public services and business and environmental protection. Since AI differs in perception from simple non-AI-based software due to its special characteristics, a separate study is necessary (Leyer & Schneider, 2021; Rzepka & Berger, 2018). Artificial neural networks are the most commonly used type of AI, and research has analyzed the potential from a conceptual perspective to foster efficiency gains (Misuraca et al., 2020), to increase public safety (Henman, 2020), and to support the use of the Internet of things (IoT) (Kankanhalli, Charalabidis, & Mellouli, 2019).

While there is great potential regarding AI in public services, the concerns of citizens regarding its growth and use present a major hurdle (Dirican, 2015; Galloway & Swiatek, 2018). Hence, understanding general public acceptance of AI in public services is of major importance

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(Kowalkiewicz & Dootson, 2019). A main distinguishing feature of how AI is perceived compared to existing software-based services is that individuals assign superior abilities to AI. On the one hand, AI is powerful as it can solve problems more accurately and is more objective; on the other hand, it is not transparent as it can develop rules that are not documented and thus reduce human control and trust (Leyer & Schneider, 2021). Despite concerns about uses of technology potentially suppressing citizens and reducing their freedom of expression (Kummitha, 2020), research has not yet covered citizens' acceptance regarding the introduction of AI into the public sector. Hence, it is important to understand the reasons for acceptance of AI in public services in general and from a practical perspective to determine how public services should be designed to take citizens' concerns into account. In short, the research questions that emerge from these considerations are, first, whether AI is accepted for (specific and general) services in the public sector, and second, why AI is accepted or rejected in that context.

To address these research questions, we adopt a policy-capturing scenario research design to analyze the acceptance of AI by citizens in six different scenarios that correspond to common groups of public services. Adopting behavioral reasoning theory (BRT) (Westaby, 2005), we question participants regarding their acceptance of AI compared to humans providing the same services, and we analyze which reasons have a particular influence on the acceptance of AI. We contribute to the literature on government by deepening understanding of the role of AI in public services. The results provide insights into why citizens accept AI in public services and highlight which factors are relevant and non-relevant.

The structure of the paper is as follows. In Section 2, the foundations of AI in public services are presented. In Section 3, the theory applied to understand why AI is adopted in public services is discussed, and our hypotheses are stated. Section 4 covers the sampling, questionnaire, and structural modeling approach. The results are presented in Section 5. We conclude the article in Section 6 with a discussion of the findings, their theoretical and practical implications, and limitations and future research.

2. AI in public services

2.1. Types of public services

A variety of public services is provided by public institutions to citizens. Such services primarily concern health, housing, education, social assistance, and unemployment (Walsh, 1991). Public services are heterogeneous, which is reflected in the different categorizations that can be found in the literature. Hajkowicz et al. (2019) categorized public services into three groups: natural resources and environment; health, aging, and disability; cities, towns, and infrastructure. Afonso, Schuknecht, and Tanzi (2005) categorized public services into four groups: administrative, education, health, and public infrastructure, while Diepart et al. (2016) distinguished between health, education, public administration, social, and security. Health appears consistently in these three categorizations, while infrastructure, administration, and education are each mentioned twice. Given the different approaches, we combine them in a way that covers all relevant dimensions but avoids a scattered detailed classification. First, the area of administration, social, and education affairs encompasses all services that represent citizens administratively and socially, and which can be seen as a general support to organize personal life. Second, the area of security and health covers all services that support maintaining the physical integrity of citizens, thus including health and safety. Third, the area of infrastructure includes services that support the economic and organizational interests of the national economy.

Further, these public services can be distinguished into specific and general services according to how they are provided (Halaris et al., 2007). Specific public services are explicitly requested by citizens and have an impact on only one or a few citizens. General public services are provided by the government without specific request, and concern all or the majority of citizens. This distinction is supported by uniqueness theory (Snyder & Fromkin, 2012), according to which specific services focus on direct interaction and specific provision for an individual, whereas general services are not directed at specific individuals. Hence, taking into account the topic areas and the way services are provided, we can distinguish six types of services (see Table 1).

Independent of category, public services differ from private services in four main ways. First, there is no competition between service providers in the public sector. Governmental institutions can decide which institution or level (federal or municipal) is responsible for offering a certain service, but only one institution offers the service. Hence, individuals in their capacity as citizens have no choice between services or service providers (Cox, 2008). Second, the goal of public institutions is to achieve effectiveness, efficiency, and equity through their services, whereas private companies pursue efficiency and cost reduction (Azmi, Ahmad, & Zainuddin, 2009; Radnor & Osborne, 2013). Public services are often offered even where there is no efficiency or in situations characterized by high costs due to legal obligations; accordingly, they are perceived differently by individuals. Third, determining customer value is difficult for public services, as citizens are typically not the principal, but rather applicants or recipients without specific demands, especially for public goods such as waste disposal or security provided by the police and military. Hence, it is more difficult to measure customer value, for example, in terms of satisfaction(Radnor & Osborne, 2013), for public services than for private services. Fourth, the results of decisions in the public sector must be fully justifiable. This accountability to citizens is not required in the private sector and therefore represents another crucial difference between the sectors (Sager, Thomann, & Hupe, 2020).

2.2. Characteristics of AI

The term "artificial intelligence" was first used in 1956 to describe technologies that possess capabilities and functions that are primarily associated with human intelligence (Galloway & Swiatek, 2018). AI-based software has intelligence-requiring capabilities, such as problem-solving, reasoning, perception, and communication (Russel & Norvig, 2010; Rzepka & Berger, 2018). Unlike non-AI-based software, AI-based software is self-learning, which means that programming in advance is not necessary (Leyer & Schneider, 2021). The software can deduce the rules for decision-making by means of machine learning from the data processed (Martin, 2019; Zuboff, 2019). Often, technology is divided into rule-based and data-driven (Janssen, Hartog, Matheus, Yi Ding, & Kuk, 2020). Depending on how the technology is used, this distinction can have a big difference on individual perceptions and ultimately on acceptance (Thiebes, Lins, & Sunyaev, 2021). AI-based software retrieves important information from large data sets and can recognize patterns that are undetectable by humans (Thierer et al., 2017). This can help to identify risks and problems that may otherwise have gone unnoticed (Galloway & Swiatek, 2018). In addition, AI works faster than human processing, for example, when analyzing data (Alexopoulos et al., 2019). If not programmed or trained to do otherwise, AI can process data more objectively than humans and without the influence of emotions (Dietvorst, Simmons, & Massey, 2015; Leyer & Schneider, 2021). However, AI processing is often a black box since it is

Table 1
Six types of public services.

Specific services	General services
Specific administration, social and education	General administration, social and education
Specific security and health	General security and health
Specific infrastructure	General infrastructure

difficult to determine which logic an AI has learnt for processing information (Sun & Medaglia, 2019; Thiebes et al., 2021).

Collaboration between AI and humans is possible for decision support and decision-making (Leyer, Oberlaender, Dootson, & Kowalkiewicz, 2020). For example, technology can classify relevant information and make it available to humans for further processing. Humans can then use the information to formulate hypotheses that can be used to make decisions (Alexopoulos et al., 2019; Jordan & Mitchell, 2015). In contrast, an autonomous decision maker evaluates options, makes decisions, and assesses the results (Leyer et al., 2020). Although AI systems can be further classified from a technical perspective (e.g., deep learning, rule-based, supervised, and unsupervised), the focus of this article is on how they are perceived by individuals without specialist knowledge, and such classifications are therefore not elaborated here.

3. Theoretical approach

3.1. Theoretical framework

In order to explain the acceptance or rejection of AI in public services, we adopt BRT proposed by Westaby (2005). The theory is based on the theory of reasoned action (TRA) proposed by Fishbein and Ajzen (1975) and the theory of planned behavior (TPB) proposed by Ajzen (1991). Unlike these predecessors, BRT incorporates reasons for and against behavior in terms of intention. According to the unified theory of acceptance and use of technology 2 (Venkatesh, Morris, Davis, & Davis, 2003; Venkatesh, Thong, & Xu, 2012), it is possible to determine acceptance by means of the intention to use. For this reason, we adapt BRT so that intention to use represents acceptance, which is a similar construct (Fishbein & Ajzen, 2010). The constructs of attitude, subjective norm, and perceived behavioral control (termed global motives) are adopted from TPB and extended to include as antecedents the constructs of reasons for and reasons against behavior (Westaby, 2005; Westaby, Probst, & Lee, 2010). Fig. 1 provides an overview of the theory.

Analysis of reasons can provide an additional explanation of why individuals choose a particular behavior. Reasons for and against the behavior influence global motives, especially attitudes, through strong reasons that support and justify the choice (Hsee, 1996). In this way, reasons have a direct impact on intentions, as well as an indirect impact mediated by global motives (Kunda, 1990; Steele, Spencer, & Lynch, 1993). The reasons for and against behavior can be qualitatively different and may influence individuals differently (Westaby et al., 2010).

In BRT, attitude, subjective norm, and perceived behavioral control are referred to as global motives, which are seen as comprehensive substantial factors that consistently influence intentions regarding behavior (Wanberg, Glomb, Song, & Sorenson, 2005; Westaby, 2005). Behavioral attitudes represent the individual's own attitude toward this behavior and include an assessment of the individual's intended behavior (Ajzen, 1991). The subjective norm represents the orientation of an individual toward the social environment's assessment of the planned behavior (e.g., perceived social pressure for the behavior). In most cases, an attempt is made to meet the requirements and expectations of the social environment (Claudy, Peterson, & O'Driscoll, 2013; Hackman & Knowlden, 2014). Perceived behavioral control is the degree of control that the individual perceives in relation to how easy or difficult it is to perform the intended behavior (Armitage & Conner, 2001; Hackman & Knowlden, 2014). Behavioral intention reflects the extent to which an individual is willing to show a certain behavior (Ajzen, 1991). In summary, intention and subsequent behavior require comparison and selection between global motives (Sheppard, Hartwick, & Warshaw, 1988).

3.2. Related work

There is great potential for the use of AI in the public sector (Kowalkiewicz & Dootson, 2019). By integrating AI into public services, the satisfaction of citizens can be increased through better service delivery, and productivity can be improved through process automation and decision support (Sun & Medaglia, 2019). Use of AI enables a more efficient allocation of resources and can optimize staffing levels (Eggers, Schatsky, & Viechnicki, 2017; Kankanhalli et al., 2019). However, the use of AI in the public sector has not been the focus of much research (Sun & Medaglia, 2019), and previous studies have discussed the potential from a conceptual implementation perspective without considering the issue of acceptance by citizens. Ideas can be found in the areas of healthcare, transportation, education, and security (de Sousa et al., 2019), and there are many examples of how AI can be implemented to support public services (Rosemann et al., 2020). There are even projects in which AI has been integrated into public administration (Misuraca et al., 2020) and into the health sector (Yang, Ng, Kankanhalli, & Yip, 2012). Nevertheless, no findings on their acceptance have been reported.

There is, however, some initial research on acceptance in the public sector. König and Wenzelburger (2020) considered appropriate conceptual mechanisms for avoiding negative impacts of the introduction of AI at different levels of public policy in a democracy. Aoki (2020) studied public trust in AI-based chat offerings in public services. Their empirical results showed that the acceptance of objects or events was higher if they were not completely new; trust was lower in the area of parental support than in the area of waste separation. With regard to negative aspects of AI from a citizen perspective, results regarding COMPAS software, used to predict the likelihood of recidivism among offenders, have shown it to be unreliable and racially biased (Dressel & Farid, 2018; Kankanhalli et al., 2019). Schaefer et al. (2021) identified obstacles regarding employees, such as perceived pressure from society or industry and perceived technical competence at the municipal level, that should be considered when implementing AI. Sun and Medaglia (2019) examined challenges with regard to aspects of organization, management, and data that need to be considered when implementing AI in the medical sector. Stakeholders (government policymakers, hospital managers/doctors, and IT firm managers) perceive different challenges in relation to AI. At the same time, they have different views on AI, which may complicate implementation. Summarizing, it can be stated that AI is perceived differently to existing software as the main underlying feature recognized by individuals is its ability to adapt its behavior to circumstances. Individuals consider AI to be smart in processing large amounts of data and making decisions adapted to the context that humans are not capable of to this extent (Leyer & Schneider, 2021).

3.3. Hypotheses and research model

When it comes to types of AI-based software, Martin (2019) noted

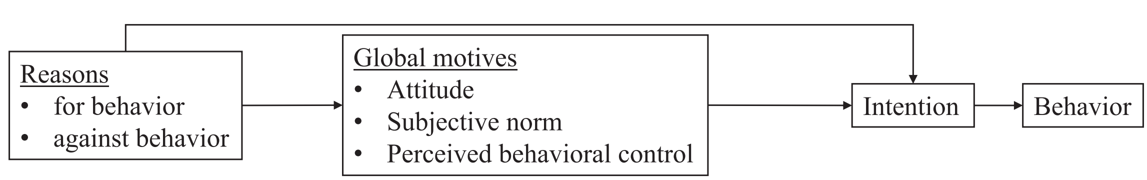

Fig. 1. Behavioral reasoning theory (adapted from Westaby (2005).

that the use of AI is particularly preferred for decisions that have a greater impact on society. This distinction matches our separation of public services into specific and general services. It is also in line with the idea of the level of situational awareness, which is very likely to be higher for specific services and lower for general services. Schneider and Leyer (2019) investigated the relationship between situational awareness and the delegation of decisions to AI. Hence, based on the conceptual insights of Martin (2019) in combination with the results of Schneider and Leyer (2019), the following hypotheses have been developed to investigate the first research question:

H1a. *For a specific service, citizens' acceptance of AI is lower than their acceptance of employees delivering the same service.*

H1b. *For a general service, citizens' acceptance of AI is similar to their acceptance of employees delivering the same service.*

With regard to a deeper understanding of why humans accept AI, BRT emphasizes the relevance of global motives. Empirical research on the three variables can be found for AI as follows. Lichtenthaler (2019) showed that acceptance depends on the individual's attitude to the technology and the specific situation. Citizens with a positive attitude toward new technologies are also likely to accept AI. On the one hand, acceptance is often present when citizens benefit from the application. When AI is used, citizens can benefit from rational decisions that do not take account of emotions and empathy. On the other hand, if an individual has a negative attitude toward AI and a preference for interaction with humans, the individual will overlook the benefits of using AI. At the same time, the individual's attitude may change depending on the situation and context (Lichtenthaler, 2019).

Social trust, which can be defined as the acceptance of a population, can influence the organization of work and production processes (Gur & Bjørnskov, 2017). According to Chen, Guo, Gao, and Liang (2020), citizens with increased trust in governments tend to associate AI with a more positive experience. Acceptance is equated with behavioral intention and indicates whether the respondents have a positive relation to AI in public service. Therefore, construct acceptance is of particular importance in this research, and intention is equated with construct acceptance (Abrahão, Moriguchi, & Andrade, 2016). In line with BRT and the few insights from the initial empirical research, we formulate our second hypothesis as follows:

H2. *(a) Attitude, (b) subjective norm, and (c) perceived behavioral control are positively related to acceptance of AI.*

Research in other domains has already examined the influence of reasons on global motives (Norman, Conner, & Stride, 2012; Sahu, Padhy, & Dhir, 2020; Westaby, 2005; Westaby et al., 2010). It has been argued that global motives can change depending on the reasons for or against a behavior, in this case, for or against the acceptance of AI in public services. Accordingly, the influence of reasons on attitude, subjective norm, and perceived behavioral control are hypothesized as follows:

H3. *Reasons for acceptance are positively related to (a) attitude, (b) subjective norm, and (c) perceived behavioral control.*

H4. *Reasons against acceptance are negatively related to (a) attitude, (b) subjective norm, and (c) perceived behavioral control.*

Reasons for and against acceptance explain the incremental variance of acceptance to the global motives emphasized by BRT. The only empirical evidence in this regard is from Sivathanu (2018), who used BRT to investigate the adoption of IoT-based wearables in healthcare and found that the reasons against their adoption have a stronger influence on adoption intention than the reasons for it (Sivathanu, 2018). Since there is no evidence to the contrary, we follow BRT and formulate our final set of hypotheses as follows:

H5. *(a) Reasons for acceptance have a positive influence on acceptance of AI; (b) reasons against acceptance have a negative influence on acceptance of AI.*

H6. *(a) The influence of reasons for acceptance on the acceptance of AI is positive and mediated by global motives; (b) the influence of reasons against acceptance on the acceptance of AI is negative and mediated by global motives.*

Fig. 2 provides an overview of the research model.

4. Materials and methods

4.1. Research design and measures

We used a policy-capturing research design which includes manipulations and captures decision-making as well as the subsequent reactions of participants (Webster & Trevino, 1995) and has been used to analyze the acceptance of AI (Leyer & Schneider, 2019). According to the outlined grouping of public services, and following Hajkowicz et al. (2019), we chose six services to represent the respective categories (for details see Appendix A): (1) specific administration, social, and education: exhibition; (2) specific security and health: life-threatening disease; (3) specific infrastructure: waste management; (4) general administration, social, and education: youth aid in hot spots; (5) general security and health: bushfires; and (6) general infrastructure: bridge. In all scenarios, the AI-based software was presented in an embedded way (Glikson & Woolley, 2020). Each participant was confronted with one scenario only, which was assigned at random. In each scenario, the setting was described and participants had the choice between a human and an AI-based software performing the public service.

In addition to acceptance (measured using one item on a nominal scale), we measured the following variables (the detailed questionnaire can be found in Appendix B). The reflective constructs of attitude (measured using five items on a 5-point Likert scale), subjective norm (four items on a 5-point Likert scale), and perceived behavioral control (four items on a 5-point Likert scale) were formed following the method of Fishbein and Ajzen (2010). The formative constructs of reasons for the behavior (11 items on a scale consisting of "Not an influential reason," "Influential reason," and "Very influential reason"; (Westaby, 2005) and reasons against the behavior (12 items on the same scale) were formed from the results of a number of scientific studies (Aggarwal & Mazumdar, 2008; Sciutti, Mara, Tagliasco, & Sandini, 2018; Shibl, Lawley, & Debuse, 2013). The survey was supplemented with demographic data regarding age, gender, and a self-assessment of the participants' experience with algorithms (one item on a 7-point Likert scale).

4.2. Sample

To investigate citizens' acceptance of AI in the public sector, we gathered data in April and May 2020 using Clickworker, a platform similar to Amazon MTurk. Based on recommendations for online survey platforms, attention checks were built in (Goodman, Cryder, & Cheema, 2013). In particular, each participant had to correctly answer two checking questions referring to the content of the scenario in order to continue with the survey. Moreover, we asked participants whether they perceived the scenarios to be realistic. We chose Australia as the research setting, as the country is digitally advanced in the public and private sectors and its citizens can be expected to have an informed opinion on the matter (Hajkowicz et al., 2019). Participants received a payment that reflected the minimum wage in Australia at the time (identified before with a pre-test) to fill out the questionnaire. Overall, we collected responses from a total of 329 respondents. The responses for each scenario were as follows: (1) specific administration, social, and education: human: $n = 23$, AI: $n = 26$; (2) specific security, and health: human: $n = 32$, AI: $n = 19$; (3) specific infrastructure: human: $n = 29$, AI: n = 23; (4) general administration, social, and education: human: n = 26, AI: n = 26; (5) general security and health: human: n = 23, AI: $n =$

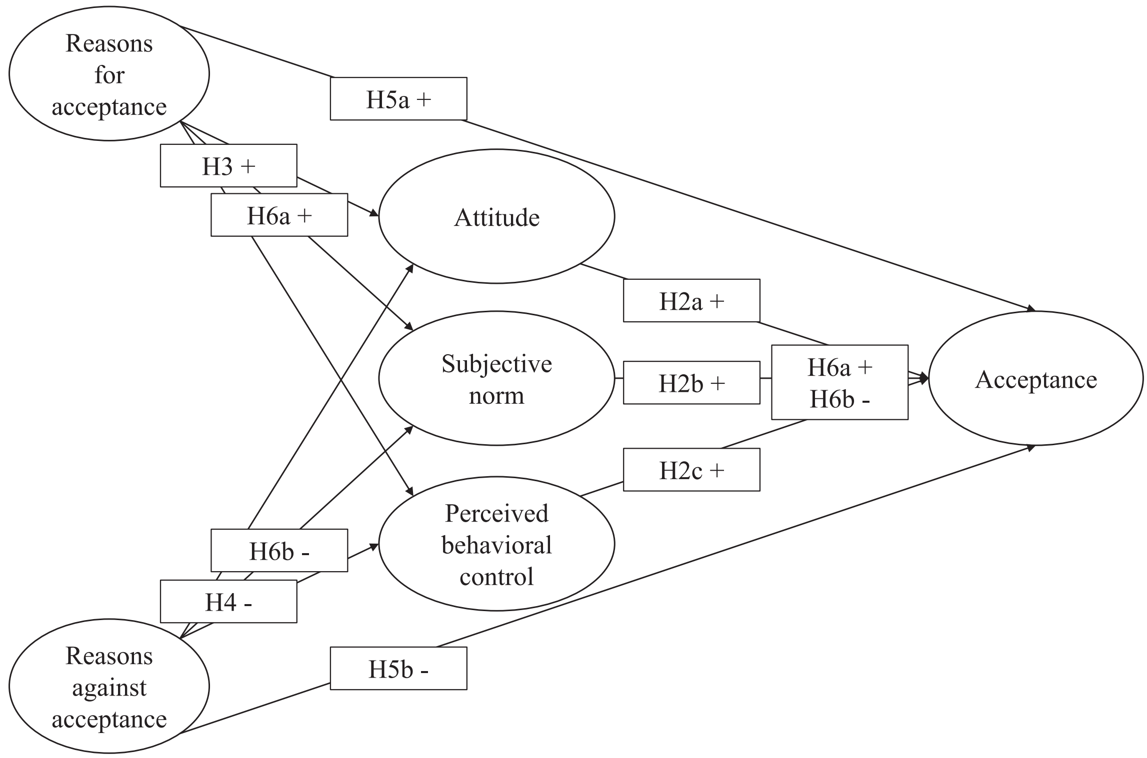

Fig. 2. Research model.

30; and (6) general infrastructure: human: n = 30, AI: n = 42.

Of the participants, 54.7% were women, 45.0% men, and 0.3% did not specify their gender. The average age was 33.20 years (SD = 10.34), ranging from 16 to 67, with 10.9% not specifying their age. Compared to the national averages of Australia, the values are similar with 50.4% of the population being female and an average age of 37.8 years (Australian Bureau of Statistics, 2020). Since our sample was gathered using an online platform, it is not surprising that its average age is lower than the national average, but our sample, with ages up to 67, covers over 90% of the adult age range. The average subjectively reported level of experience with algorithms was 3.87 (SD = 1.61).

4.3. Data analysis

In addressing the first research question and analyzing the first hypothesis, we conducted Pearson's chi-square tests to determine the acceptance of AI in the respective public services compared to humans in the same scenarios, as well as comparing the acceptance of AI between specific and general services.

For the second research question and Hypotheses 2 to 6, the method of partial least squares was used. A bootstrapping procedure with 5000 resamples was performed in SmartPLS 3.3.6 (Hair, Ringle, & Sarstedt, 2011), with specific and general services analyzed in two separate models.

The analysis of the reflective and formative measurement models was performed for validity and reliability as described in Hair et al. (2011). The reflective constructs were "attitude," "subjective norm," and "perceived behavioral control." The indicator reliability was confirmed for each construct, since the values were greater than 0.7. The composite reliability was also confirmed for the three constructs, as the value was greater than 0.7 for specific and general services (attitude Specific: 0.889, General: 0.877; perceived behavioral control Specific: 0.855, General: 0.946; subjective norm Specific: 0.954, General: 0.935) (Hair et al., 2011). Discriminant validity can also be assumed using the heterotrait–monotrait method, since all values were less than 0.9 (Henseler, Ringle, & Sarstedt, 2014).

"Reasons for acceptance" and "reasons against acceptance" were the formative constructs in the model. The multicollinearity analysis showed that the variance inflation factor for each indicator was below 5 (Hair et al., 2011). The relative and absolute importance of the indicators were checked using the loadings and weights. On the grounds of a 5% probability of error, seven indicators for the reasons for acceptance and eight indicators for the reasons against acceptance were eliminated for specific services, and one indicator for reasons for acceptance and ten indicators for reasons against acceptance were eliminated for general services.

The quality of the structural model (model fit) was checked using the standardized root mean square residual (SRMR) (Henseler, Hubona, & Ray, 2016). The values for saturated and estimated SRMR were below the threshold of 0.1 (Specific: 0.083, 0.097; General: 0.070, 0.074). Blindfolding was performed with an outlet distance of 7. The result were positive Stone–Geisser Q^2 values (acceptance Specific: 0.304, General: 0.008; attitude Specific: 0.333, General: 0.160; perceived behavioral control Specific: 0.006, General: 0.101; subjective norm Specific: 0.223, General: 0.025). Thus, the model can be considered relevant to predict the endogenous constructs (Henseler et al., 2016).

5. Results

5.1. Descriptive statistics

Table 2 provides an overview of the descriptive statistics for the whole data set and for the AI-scenarios only, as well as the respective correlations for the variables within the research model.

5.2. Hypotheses testing

First, we analyze the results with regard to Hypothesis 1. As can be seen in Table 3, there is no overall significant difference between humans and AI as potential service providers. However, if the type of public service is considered, we find support for Hypothesis 1(a), as acceptance of AI is significantly lower than acceptance of humans

Table 2
Descriptive statistics of the overall sample and correlations among variables (N = 329 resp.); M = mean; SD = standard deviation; S = specific services; G = general services.

	Human and AI		AI only (S & G)		AI only (S & G)					
	M	SD	M	SD	1	2	3	4	5	6
1: Reasons for acceptance	2.07	0.435	S: 2.01	S: 0.465	–	S: 0.119	S: 0.548***	S: 0.409**	S: 0.290*	S: 0.241*
			G: 2.17	G: 0.408	–	G: 0.218*	G: 585***	G: 0.285**	G: 0.315**	G: −0.89
2: Reasons against acceptance	1.72	0.477	S: 1.86	S: 0.575		–	S: −0.321**	S: −0.205	S: −0.005	S: −0.458***
			G: 1.79	G: 0.503		–	G: 0.028	G: 0.126	G: 0.069	G: −0.337**
3: Attitude	3.55	0.763	S: 3.32	S: 0.831			–	S: 0.509***	S: 0.236	S: −0.498***
			G: 3.62	G: 0.721			–	G: 0.391***	G: 0.308**	G: 0.064
4: Subjective norm	3.14	1.163	S: 2.90	S: 1.14				–	S: 0.173	S: −0.247*
			G: 3.23	G: 1.00				–	G: 0.069	G: −0.089
5: Perceived behavioral control	3.77	1.033	S: 3.91	S: 0.937					–	S: −0.064
			G: 3.52	G: 1.14					–	G: −0.272**
6: Acceptance	1.65	0.478	S: 1.72	S: 0.452						–
			G: 1.58	G:0 .497						–

Table 3
Comparison of acceptance rates within the scenarios.

Type of public service	Topic Area	Acceptance of Human	Acceptance of AI	Chi-Quadrat Pearson
	Overall	66.3%	63.9%	0.648
Specific		94.0%	72.1%	0.000
	Administration and social	95.7%	88.5%	0.359
	Security and health	87.5%	47.4%	0.002
	Infrastructure	100%	73.9%	0.003
General		36.7%	58.2%	0.005
	Administration and social	42.3%	53.8%	0.405
	Security and health	0.0%	10.0%	0.118
	Infrastructure	60.0%	95.2%	0.000

delivering the same specific service. The post hoc results at the level of topic area show that although there are no significant results for administration, social, and education affairs, humans are more accepted in the other two specific topic areas. We find no empirical support for Hypothesis 1(b), as, surprisingly, AI is significantly more accepted than humans in the provision of general public services. The post hoc results for the general topic areas show that AI is always more accepted than humans, although in some cases the difference is not significant.

Fig. 3 provides an overview of the results for Hypotheses 2 to 6 in relation to why AI was accepted for specific and general public services.

For Hypothesis 2, we find no empirical support for (a) attitude (Specific: 0.224, ns, f^2 = 0.038; General: 0.114, ns, f^2 = 0.009), (b) subjective norm (Specific: −0.113, ns, f^2 = 0.017; General: −0.031, ns, f^2 = 0.001), or (c) perceived behavioral control (Specific: 0.051, ns, f^2 = 0.004; General: −0.195, ns, f^2 = 0.034) for either service type. Therefore, attitude, subjective norm, and perceived behavioral control do not affect acceptance of AI in either specific or general services.

For Hypothesis 3, we find empirical support, as there is a significant

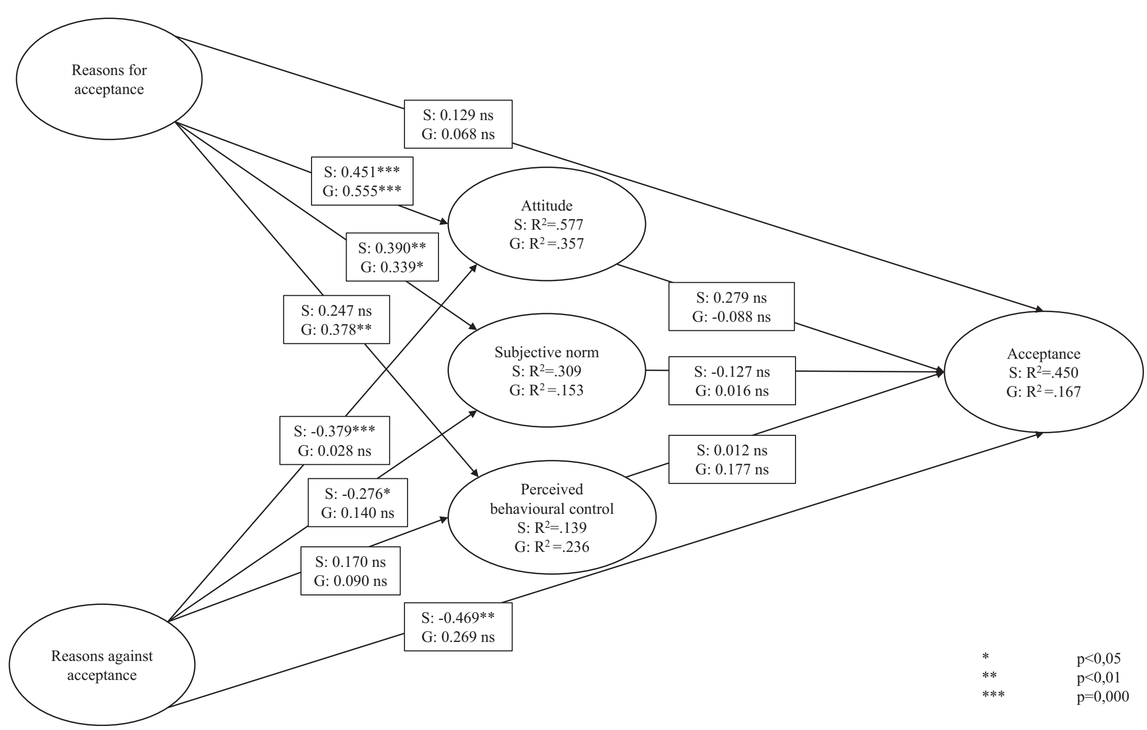

Fig. 3. Results of the research model for specific (S) and general (G) public services.

positive effect between reasons for acceptance and (a) attitude (Specific: 0.433, $p < .001$, $f^2 = 0.418$; General: 0.575, $p < .001$, $f^2 = 0.473$), (b) subjective norm (Specific: 0.389, $p < .01$, $f^2 = 0.198$; General: 0.316, $p < .05$, $f^2 = 0.103$), and (c) perceived behavioral control for general services (General: 0.390, $p < .01$, $f^2 = 0.178$), although not for specific services (Specific: 0.255, ns, $f^2 = 0.072$). Thus, for specific services, reasons for acceptance have a positive impact on attitude and subjective norm, but not on perceived behavioral control. For general services, reasons for acceptance have a positive impact on attitude, subjective norm, and perceived behavioral control.

We also find empirical support for Hypothesis 4(a) and (b) in the significant negative effect of reasons against acceptance and (a) attitude (-0.410, $p < .001$, $f^2 = 0.369$) and (b) subjective norm (-0.249, $p < .05$, $f^2 = 0.080$) for specific public services, although not for general services (4(a) -0.045, ns, $f^2 = 0.003$; 4(b) 0.133, ns, $f^2 = 0.020$). There is no effect regarding Hypothesis 4(c) (Specific: 0.268, ns, $f^2 = 0.078$; General: 0.076, ns, $f^2 = 0.007$) for either type of public service. Hence, for specific services, reasons against acceptance have a negative impact on attitude and subjective norm, but not on perceived behavioral control. For general services, reasons against acceptance do not affect attitude, subjective norm, or perceived behavioral control.

Regarding Hypothesis 5(a), we find no empirical support for a direct positive influence of reasons for acceptance (Specific: 0.113, ns, $f^2 = 0.014$; General: -0.034, ns, $f^2 = 0.001$). However, we find support for Hypothesis 5(b), because the reasons against acceptance (Specific: -0.540, $p < .001$, $f^2 = 0.331$; General: -0.271, $p < .05$, $f^2 = 0.081$) have a negative influence on acceptance of AI. Thus, for specific services, reasons for acceptance do not affect acceptance, but reasons against acceptance have a negative impact on acceptance. For general services, reasons for acceptance also do not affect acceptance, but reasons against acceptance also have a negative impact on acceptance.

For Hypothesis 6(a), we find no empirical evidence, as there is no mediation between reasons for acceptance and acceptance through global motives for either service (Specific: 0.066, ns; General: -0.020, ns). The same holds true for Hypothesis 6(b) and for the mediation between reasons against acceptance and acceptance through global motives (Specific: -0.050, ns; General: -0.024, ns). Hence, whether for specific or general services, reasons for acceptance and reasons against acceptance are mediated by attitude, subjective norm, and perceived behavioral control on acceptance of AI.

The control variables age, gender, and experience have some limited effects, and we report the significant ones. For specific public services, experience with AI-based software influences attitude (Specific: 0.262, $p < .01$, $f^2 = 0.156$). For general public services, age has a significantly negative influence on perceived behavioral control (General: -0.188, $p < .05$, $f^2 = 0.046$).

Moreover, for AI in specific services, we find an impact of the item "right of participation" regarding reasons for acceptance, and the items "possibility to make decision myself," "exceptional concerns," and "loss of trust between human and AI," have an impact on reasons against acceptance. For AI in general services, we find an impact of the items "right of participation," "according to my requirements," and "transparency" on reasons for acceptance, and the item "fear of failure" has an impact on reasons against acceptance (for details see Appendix B).

6. Discussion

With regard to the first research question, we find a surprising higher acceptance of AI. Explanations can be found in the results derived from the research model. The results regarding reasons for acceptance show that reasons against acceptance are the only explanatory factor. Risk and trust are important aspects that influence acceptance of AI systems (Tschopp & Ruef, 2018; Yanushkevich et al., 2019), and both are reflected in reasons against acceptance. The influence is higher for specific services than for general services, which is also reflected in participants' rejection of AI for specific services despite their preference for AI in general services. This result can be explained in terms of the nature of the two different types of services. Specific public services allow an individual to decide whether to use AI. In the case of general public services, an individual cannot choose whether a particular service is performed by AI or with human support. The choice exists for the individual to vote for a party in elections that either advocate for or against the use of AI in general public services as well as generating a public awareness with social pressure on administration. As general public services are more abstract (in that they go beyond the individual situation), the citizen might perceive a lower level of situational awareness, meaning they also accept an AI. Since there can be individual acceptance decisions for specific services, the opportunity to decide is relevant, and citizens want to have a choice between using AI-based software to address their concerns and resolving them with the help of a clerk.

However, the results regarding perceived behavioral control show that citizens feel that they do not have much of a choice regarding the introduction of AI. Moreover, the respondents do not see AI as being able to handle exceptional concerns. Since general services do not involve a direct interaction between citizens and AI-based software, the reasons against adoption differ and are less relevant. In general services, fear of failure is the most important reason against the acceptance of AI. The lack of interaction between citizens and the AI application may give rise to concerns that the responsible public institution will, for example, make the wrong decision as a result of incorrect application of AI-based software.

Reasons for acceptance may have no significant effect because public services are less focused on providing competitive offers. Thus, it seems that acceptance is driven when negative factors are not present, but that positive factors have a stronger influence on global motives, especially for specific services. However, the results show that positive aspects increase the feeling of perceived behavioral control for general services (i.e., the feeling of influencing the public discourse in this regard). However, as global motives have no influence on acceptance, further analysis would not be useful. The reason for this missing link may be that individual global motives do not trigger either risk or trust regarding the use of AI in public services.

When it comes to the use of AI in specific and general public services, there are different reasons for or against acceptance. On one side, the right of participation (Pisano & Verganti, 2008) was the only factor for the acceptance of AI in specific public services in our study. Thus, we agree with the findings of Pisano and Verganti (2008) that there is an opportunity for interaction to be involved in solving a specific problem. According to our research, citizens want to have a voice in the use of AI in specific public services. Therefore, they want the possibility of making decisions themselves (Aggarwal & Mazumdar, 2008). This is one of three reasons against acceptance of AI in specific public services. Exceptional concerns (Shibl et al., 2013) and the loss of trust between humans and AI (Shibl et al., 2013) are the other two reasons that impact acceptance. Thus, the acceptance of AI in specific services can be increased if the co-determination and co-creation of individuals in (exceptional) requests is given. We also support the findings of Shibl et al. (2013) with our findings that there is no loss of trust between humans and AI. If the loss of trust is prevented, then the acceptance of AI in specific services increases.

On the other side, right of participation (Pisano & Verganti, 2008), being according to their requirements (Aggarwal & Mazumdar, 2008), transparency (Glikson & Woolley, 2020), and fear of failure (Shibl et al., 2013) have an impact on the acceptance of AI in general services. As with specific services, the right of participation is an important component for the acceptance of AI in general services. Thus, with our study, we support the findings of Pisano and Verganti (2008) and Aggarwal and Mazumdar (2008), who stated that adaptation to the needs of the individual is important. Since we are looking at general public services that do not require an individual application, it can be assumed that while the needs of the general public should already be considered, they should then at best match the needs of the individual. The public sector should see itself as a service provider. In addition, transparency of the use of AI in general services is necessary to increase adoption. Among citizens, fear of failure is the only reason in our study that counters the acceptance of AI in general services. Thus, our findings support a variety of studies that view the risk of AI being a black box (e.g. Sun & Medaglia, 2019; Thiebes et al., 2021).

The feeling of the uniqueness of citizens, identified by Snyder and Fromkin (2012), is evident here for specific services. The findings, combined with the results of Schneider and Leyer (2019) for personal decision-making, are also relevant in the domain of public services. On the one hand, citizens see specific public services as more personally relevant, and they put more value on individual requests and requirements. Owing to the high situational awareness on the part of individual citizens, negative aspects are weighted more heavily, and an AI application is less likely to be accepted. On the other hand, for general services, citizens have low situational awareness, because they lack an overview. For this reason, they are more likely to accept AI applications in these services. Thus, the results of Schneider and Leyer (2019), Snyder and Fromkin (2012), and Martin (2019) are corroborated by our research.

In summary, reasons against acceptance have the greatest impact on AI acceptance for both specific and general services, as these reasons are the predominant triggers for the risk factors of such an implementation.

7. Conclusion

7.1. Theoretical implications

Our results have several theoretical implications. First, this is the first study to investigate the acceptance of AI in public services and, thus, to highlight the importance of investigating this aspect in contexts beyond the services provided by companies. Furthermore, our results show that it is important to distinguish between specific and general public services, as each type requires different factors to be taken into account in evaluating the acceptance of AI-based software.

Second, our research shows that using a policy-capturing scenario research design in conjunction with BRT provides valuable insights into the acceptance of AI in public services. The model can explain a sufficient amount of variance for both types of services and shows that the reasons against acceptance are a major reason for preferring humans in specific services. Our results confirm the findings of related studies in other domains (e.g. Sivathanu, 2018), which have shown that reasons against acceptance have the greatest influence regarding, for example, the adoption of IoT-based wearables.

Third, we contribute to the literature on governmental research from the perspective of decision-making delegation in public services as assessed by citizens. It is important not only to consider conceptual options but also to integrate citizens' concerns into design options, as their acceptance is important for governmental institutions.

7.2. Practical implications

Implementation of AI in public services has the potential to increase service efficiency and service quality for citizens (Galloway & Swiatek, 2018; Kowalkiewicz & Dootson, 2019; Misuraca et al., 2020; Rosemann et al., 2020). The difference between AI-based and non-AI-based software is that AI is self-learning and thus can manage new situations without further programming (Leyer & Schneider, 2021). In addition, intelligence-requiring capabilities, such as the recognition of previously unknown patterns, are another advantage over other non-AI-based software (Rzepka & Berger, 2018). This potential can be exploited only when AI is accepted in these services. On the basis of our results, we make a number of recommendations that will help the public sector to increase acceptance.

First, the difference between specific and general public services has to be taken into account. As acceptance of AI is higher for general public services, where topics that are more complex but also more general are addressed, it should be introduced in these types of services. Second, the adoption of AI in both types of public services is influenced by the reasons against acceptance. Hence, governmental institutions should focus their limited resources on these aspects. Third, to increase the relatively low acceptance of AI for specific services, the reasons against acceptance identified here should be analyzed, and methods for addressing these concerns should be developed.

For specific services, these public services should be provided by humans more than by AI. However, AI should not be completely excluded from these services, as there are certainly tasks that AI can perform. The public sector should ensure that citizens have a voice in service delivery when implementing AI. For this purpose, a possibility should be established that allows interaction in the case of unusual concerns. At the same time, care should be taken to build trust between the AI and the citizen.

For general services, these public services could be provided by an AI. When implementing AI in these services, the public sector should ensure that AI technology and its interaction with citizens is presented in a transparent and easy-to-understand manner. This can be done, for example, by explaining advantages and disadvantages, and opportunities and risks during citizens' question time or in online portals. Another issue is the customization of AI-generated services to the requirements of citizens. This can be ensured, for example, through citizen initiatives. A higher level of engagement with citizen initiatives could lead to more citizens participating and then actively shaping them. In this way, citizens also have the opportunity to express their own needs in general public services. Addressing the fear of failure is a key factor contributing to the adoption of AI in general services. Since there is usually no direct interaction in general services between the actors, it is not as necessary to make the services easy to use. However, it is important to clearly educate people about the technology and services to minimize the fear of failure.

Further practical implications in terms of AI representation can be distinguished at the federal and municipal levels. The federal level is characterized by its remoteness from the individual citizen. In particular, reducing the fear of failure when using AI in federal services can increase adoption. To reduce fear, AI applications should be as transparent, objective, and comprehensible as possible (König & Wenzelburger, 2020). Achieving this will involve, among other things, education and the identification and correction of biases from past data (Baeroe, Miyata-Sturm, & Henden, 2020; Henman, 2020).

The municipal level, in contrast, is characterized by in-person interactions with citizens. Hence, particular consideration should be given to the reasons against acceptance of AI in municipal services. Public institutions should provide citizens with a choice between AI and employees (Aggarwal & Mazumdar, 2008; Baeroe et al., 2020; Shibl et al., 2013). Moreover, care should be taken to ensure that citizens with exceptional concerns have the opportunity to receive individual counseling and, if necessary, to clarify their concerns with an official (Shibl et al., 2013). Lack of trust (according to the non-significant reasons against acceptance) remains an issue with regard to AI (Tschopp & Ruef, 2018). Hence, we conclude that collaboration between humans and AI can be useful without decreasing the trust of citizens (Shibl et al., 2013). If acceptance among the population is to be higher and errors are to be reduced as far as possible, citizens should be involved in a transparent implementation process.

7.3. Limitations and future research

As with any research, there are several limitations to note. First, the results may differ according to the scenario. In the present study, the scenarios were chosen in line with criteria from the literature, but the participants may have had different personal experiences leading to different results. Hence, other examples within the categories should be tested to increase generalizability. Second, the results may be influenced by which level of government offers the services. Hence, trust in different governmental institutions should be included in future analyses. Third, despite a careful compilation based on the literature, essential reasons for or against acceptance may be missing from this analysis, and future studies should seek to identify and include these. Fourth, the empirical data were gathered from Australian citizens using an online platform leading to a bias of a lower mean age in the sample compared to the population, but still covering a wide age range. Additionally, the sample may not be representative of citizens of other countries. Hence, the study should be repeated in other countries. Fifth, the sample is relatively young and the self-assessment of experience with AI is relatively high. It could be that this is an unrepresentative, tech-savvy sample. Sixth, the scenarios have the same output regardless of whether the AI or the human is performing the service. It can be assumed that the AI will provide faster and possibly better service than humans could. Therefore, citizens may accept public services not because of AI but despite AI. Seventh, we have not investigated acceptance in the case of human–AI collaboration. This would make it possible to investigate different levels of automation. Eighth, we focused on AI-based software that performs the same activities as humans. However, AI-based software has the potential to deliver a range of public services, including some that do not yet exist, and future research should take account of these possibilities. Ninth, the AI-based software under study was presented in an embedded form. Different results might be obtained in connection with virtual or robotic AI-based software solutions, and future research should analyze these alternatives. In addition, no further explanation was given as to whether the software used was rule-based or data-driven. This can also have a major impact on decisions. Moreover, in order to our findings, the coefficient of determination for AI in specific services is $R^2 = 0.450$ and for AI in general services is $R^2 = 0.167$, suggesting that there are other factors that influence adoption that we have not looked at before. Further research is therefore essential to fill this knowledge gap. Furthermore, we have found that the adoption of AI in specific services can be increased if the co-determination and co-creation of individuals in (exceptional) requests is given. For this reason, deep research should take place on how these aspects can be implemented. Future research should consider the transparency of AI and individual requirements of society for AI in general services. Finally, although we focused here on citizens, other stakeholders in public services should be surveyed regarding their acceptance of AI. Services are conducted in co-creation, and thus it is important that all parties should accept the use of AI-based software.

CRediT authorship contribution statement

Tanja Sophie Gesk: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Resources, Writing – original draft, Writing – review & editing, Visualization, Project administration. **Michael Leyer:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

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

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Appendix A. Scenarios

A.1. *Exhibition (Specific administration, social & education)*

You are in an exhibition in a museum which is about your favorite topic. You paid 10 AUD and the exhibition is open for three more days. Since you already know a lot of information about the topic, you want to get in-depth knowledge about that exhibit.

Suddenly, there is a *curator/ computer screen with artificial intelligence-based software* next to you talking to you whom you haven't noticed before. While the curator answers your question, you will get into conversation and learn more interesting information about the topic.

A.2. *Life-threatening disease (Specific security & health)*

You are suffering from a life-threatening disease. You have had 5 different symptoms for three months. Your illness is complicated and the drugs to cure it are very expensive. The medication should be selected based on your medical history, which minimized future treatment costs and side effects.

The *doctor/ artificial intelligence-based software* checks your current state of health and takes the available health data of your family into account when deciding on the right medication.

A.3. *Waste Management (Specific infrastructure)*

You live in a city with many inhabitants. Your residential area consists of many small streets. You are living in Stephens Rd 11 and there are three other tenants in your house.

Every week a *garbage truck with two people/ garbage truck with artificial intelligence-based software* empties the individual garbage bins.

A.4. *Youth Aid in hot spots (General administration, social & education)*

You live in a potential hot spot in a big city. Your area is known for rioting youths. Around 1500 young people currently live in this area. Parents are afraid to let their children play outside after eight o'clock in the evening.

Street workers are to be deployed to contain the problem. However, only a limited number of street workers are available in the city. The City Hall, on the recommendation of *trained personnel/ artificial intelligence-based software*, should send the street workers to the worst affected residential areas.

A.5. Bushfires (General security & health)

You live in a small cottage, which is close to a forest. You enjoy the view in the sun, but suddenly you remember that it is bushfire season. It has been very hot for 4 weeks and the short rain showers around ten minutes have not reduced the fire risk. You wonder if, where and when a bush fire might break out.

You inform yourself about the data of the Australian State Weather Service Bureau of Meteorology. The information is based on measurements and calculations by *meteorologists/ sensors and weather stations with artificial intelligence-based software*. The information is always up-to-date. Currently the Fire Danger Rating is "Severe". There is a high risk of an uncontrollable fire in your area.

A.6. Bridge (General Infrastructure)

You drive your car to work over a bridge every day. The bridge is 888 m long. You need to get to work around thirty minutes. Since there is no other way to get to work, you want the bridge to last as long as possible.

A team of engineers/ The entire bridge is equipped with sensors of artificial intelligence-based software, inspect the condition of the bridge at regular intervals. Maintenance measures are only carried out if weak points can be seen. By using this information, costs can be minimized and traffic obstructions can be reduced.

Appendix B. Questionnaire with results (S = specific services, G = general services)

Variables	AI in S	AI in G
Reasons for acceptance		
−1- "According to my requirements."	0.213 ns	0.340*
−2- "Usefulness"	0.223 ns	0.058 ns
−3- "Decision support"	not used	−0.073 ns
−4- "Support for my own knowledge expansion"	0.396 ns	−0.005 ns
−5- "Time saving"	not used	−0.123 ns
−6- "Transparency"	not used	0.418*
−7- "Control"	not used	−0.091 ns
−8- "Management"	not used	0.307 ns
−9- "Productivity increase"	not used	0.188 ns
−11- "Right of participation"	0.554**	0.371*
Reasons against acceptance		
−1- "Possibility to make decisions myself"	0.665***	0.595 ns
−2- "Exceptional concerns"	0.773***	not used
−3- "Loss of trust between human and AI"	−0.552**	not used
−5- "Fear of Failure"	not used	0.727*
−11- "Confidentiality"	0.018 ns	not used
Attitude		
−1- "The use of the presented AI is beneficial."	0.291***	not used
−2- "The use of the presented AI is satisfactory."	0.281***	0.287***
−3- "The use of the presented AI is important."	0.173***	not used
−4- "The use of the presented AI is gratifying."	0.263***	0.430***
−5- "The use of the presented AI is pleasing."	0.255***	0.457***
Subjective Norm		
−1- "Individuals which have an influence on me, advise me to use the presented AI."	0.264***	0.305***
−2- "Individuals that are important to me, advise me to use the presented AI."	0.282***	0.289***
−3- "Individuals whom's opinion I value, advise me to use the presented AI."	0.257***	0.310***
−4- "Individuals in a similar situation like me, advise me to use presented AI."	0.291***	0.220*
Perceived behavioral control		
−1- "It is in my control to use the presented AI."	0.390*	0.248***
−2- "It is mainly up to me to use the presented AI."	0.415 ns	0.283***
−3- "I am convinced that I can use the presented AI."	0.013 ns	0.283***
−4- "If I really want to, I can use the presented AI."	0.352*	0.294***

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