



Understanding citizen perceptions of AI in the smart city

Anu Lehtiö¹ · Maria Hartikainen¹ · Saara Ala-Luopa¹ · Thomas Olsson¹ · Kaisa Väänänen¹

Received: 18 May 2021 / Accepted: 6 April 2022
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Abstract

Artificial intelligence (AI) is embedded in a wide variety of Smart City applications and infrastructures, often without the citizens being aware of the nature of their “intelligence”. AI can affect citizens’ lives concretely, and thus, there may be uncertainty, concerns, or even fears related to AI. To build acceptable futures of Smart Cities with AI-enabled functionalities, the Human-Centered AI (HCAI) approach offers a relevant framework for understanding citizen perceptions. However, only a few studies have focused on clarifying the citizen perceptions of AI in the context of smart city research. To address this gap, we conducted a two-phased study. In the pre-study, we explored citizen perceptions and experiences of AI with a short survey ($N=91$). Second, scenario-based interviews ($N=7$) were utilized to gain in-depth insights of citizen perceptions of AI in the Smart City context. Five central themes were recognized: (1) I don’t like *them* monitoring me, (2) I want maximum gain for minimum effort, (3) I don’t want AI to mimic people, (4) I’ll avoid using AI if I consider the risk too high, and (5) I don’t need to be concerned about AI. These offer an idea of human-centered requirements worth considering while designing AI applications for future Smart Cities.

Keywords Human-centered AI · Citizen AI perceptions · Everyday AI · AI in the smart city

1 Introduction

More than half of world’s population live in urban areas and the number is growing (UN 2020). This brings several challenges to cities, such as traffic congestions, infringement of privacy, environmental degradation, and overloaded infrastructure (Allam and Dhunny 2019). In response, cities are focusing on becoming “smarter” in the effort to meet citizens’ evolving needs and to ensure environmental, social, and economic sustainability (Lytras et al. 2019).

AI has already proved to be effective in, e.g., smart traffic stops, autonomous cars, traffic congestion prediction, education, and citizen participation (Lytras et al. 2019). Still, utilizing AI poses a myriad of challenges, e.g., the possibility of biases, difficulties in accessing the services, or their overall availability. A current example of local endeavors to resolve issues such as these is Finland’s Artificial Intelligence Program AuroraAI. The program aims to build a network based on human-centered operating model in which AI helps citizens and companies to utilize and discover, e.g., public services efficiently (Finnish Ministry of Finance 2021).

Due to AI’s increasingly ubiquitous and evolving nature, it can operate in a way that is not transparent and that can lead to lack of trust and confusion among the citizens (Goebel et al. 2018). HCAI offers a view where the focus is on the ethics of AI, citizens’ needs, perspectives, their acceptance of technology-based services, and the wider sociocultural context (Bond 2019; Ford 2015; Ismagilova et al. 2019; Riedl 2019; Xu 2019). Hollands (2008) echoes these sentiments by emphasizing that progressive smart cities need to start with people and the human capital, rather than blindly believing that information technology (IT) itself can automatically transform and improve cities.

✉ Anu Lehtiö
anu.lehtio@tuni.fi

Maria Hartikainen
maria.hartikainen@tuni.fi

Saara Ala-Luopa
saara.ala-luopa@tuni.fi

Thomas Olsson
thomas.olsson@tuni.fi

Kaisa Väänänen
kaisa.vaananen@tuni.fi

¹ Information Technology and Communication Sciences, Tampere University, Tampere, Finland

In this study, we adopted a three-dimensional approach: 1. HCAI provides the subject for our study: the people affected by AI. We investigate citizen perceptions of Smart City AI and its viable, possibly odd or inept features. The citizen viewpoint in this study is that of a service user (Cowley et al. 2018). 2. The Smart City provides the context for the study: we draw our examples of AI use in everyday life from Smart City services. 3. Acceptance provides the motivation for the study: what kind of clues citizen perceptions can offer in terms of (e.g., context sensitive, preference-related) elements of acceptable urban AI. The main research questions are: What are citizens' perceptions of intelligent services in the Smart City? Which AI-specific attributes of these services are deemed desirable or undesirable?

This study was conducted in two phases. First, a pre-survey was employed to form an initial understanding of general citizen AI perceptions. Next, scenario-based interviews were conducted to gain understanding of the more specific preconditions for AI use in the Smart City. The main contributions of this paper are thus the citizen AI perceptions and concrete requirements related to AI use in everyday life.

In the following chapter, we present prior studies related to our findings. In Sects. 3 and 4, we introduce the methodology and results of the pre-survey and the interviews, respectively. In Sect. 5, we summarize our findings, discuss them in relation to relevant previous research, and suggest ideas for future work.

2 Related work

In this study, AI's presence in citizens' lives is examined via Smart City services and applications. Thus, the focus here is on recent research on citizen attitudes, expectations, and perceptions related to the seemingly smart services in urban environments. The findings from these studies were grouped into three categories based on the types of preferences they pose to accepting AI-based Smart City services: 1. Citizens' preferences for Smart City services, 2. Citizens' preferences for AI-based service systems, and 3. Citizens' role in relation to Smart City services.

2.1 Citizens' preferences for smart city services

The overall requirement for utilizing AI-based services is safety. Citizens expect governments and technology companies to manage AI-related risks carefully (Zhang and Dafoe 2019). Risks that could affect many people such as breaches in data privacy, surveillance, and digital manipulation were given priority. Kerr et al. (2020) concur: AI's possible, wider societal impacts (dehumanization, inequality, and job losses) were highlighted. However, these types of general perceptions can echo notions that are adopted via

informal mechanisms such as films, current media coverage, and sporadic expert opinions. Thus, they do not necessarily represent the perspective of personal, everyday use (Kerr et al. 2020; Neri and Cozman 2019).

Citizens seem to favor services that aim to maintain their sense of safety and stability in their social environment and make their everyday life easier (Ji et al. 2021). In similar vein, Lytras et al. (2019) suggest that the service's purpose of use can influence citizens' acceptance intention. Services that promote communal bond or activity (via, e.g., news), that support citizens' personal interests and well-being (access to learning and training resources, smart, high-quality healthcare), and encourage development in urban environments (innovation, entrepreneurship) are deemed expedient. Still, Lytras et al. (2019) identify a possible source of bias. The participants for their study were highly educated and adept at using current Smart City services.

To use Smart City services, citizens need to be assured that their right for privacy is guaranteed and that the cost of these services does not outweigh their benefits (Habib et al. 2020). Additionally, citizens must be able to trust that urban service technologies (UST) have proper safeguards in place and the owner of any UST takes full responsibility for any type of insecurity within a service. A service needs cater to a real need, and it must be seen as personally valuable. Finally, the users need to feel confident in being able to easily become skillful in using USTs and to expect that the software is user-friendly (Sepasgozar et al. 2019).

The overall acceptance and willingness to use Smart City services appears to be based on generic needs and principles, such as safety and privacy (Fagbola and Thakur 2019). While these findings can elucidate the motivational aspects for accepting Smart City services, they offer little in terms of how these aims should be met in relation to particular application areas and ways these AI-based services function concretely.

2.2 Citizens' preferences for AI-based service systems

As Smart City services cover an extensive number of various application areas and AI-based technologies, case studies can provide basic understanding of what type of needs citizens have for commonplace AI-based technologies and the ways they function within Smart City services.

San Martín's et al. (2020) study on intelligent parking system highlights the importance of security-related attributes the system enables. As the security information (e.g., one's car being moved without permission) was prioritized, an immediate and detectable notification was due. This was translated into a more generic requirement to establish the key features for any service and seek to ensure their consistent quality. Support in time-sensitive needs such as travel

requires the service to deliver correct, up-to-date information promptly, and enable reporting possible inaccuracies (Ashfaq et al. 2020; Kuberkar 2020). Additionally, individualization was recognized as essential for perceiving the service as able and reliable (Kuberkar 2020).

Riveiro and Thill (2021) argue that any explanation that AI-based systems give for their actions needs to be intelligible, and thus be based on a model of a particular end-user. A complementary view related to proactive systems suggests that these systems need to adjust their proactivity level according to the character of the application area (e.g., when dealing with sensitive health data) and user preferences (Meurisch et al. 2020). Kocielnik et al. (2019) address the requirements that the probabilistic nature of AI (e.g., in natural language processing) poses. Services based on these types of systems should tell the users directly how accurate they are, support users' perception of understanding what is happening, and offer them ways to directly impact the system hence strengthening the sense of being in control.

In addition, AI should not be treated as exchangeable with humans in teamwork and interaction between humans and AI-systems. Instead of trying to “conceal” AI, the teamwork would benefit from building on its strengths such as high accuracy. (Shneiderman 2020; Zhang et al. 2020). Additionally, Human–AI teamwork can be enhanced by meaningful and enjoyable exchange e.g., via game-like activities and reciprocal messaging that allow mutual understanding to develop (Ischen et al. 2020; Zhang et al. 2020). Still, if the interaction, for example the bidirectional exchange, is experienced as odd, it can lead to a lack of trust and thus rejecting a service (Duffy and Zawieska 2012). Consequently, possible linguistic elements, such as the formality of the language, politeness, professionalism, or personality cues, need to be considered (Ischen et al. 2020).

These findings highlight the overall need to consider how any Smart City service can—by learning and adapting, recognizing and prioritizing application area specific requirements, and by figuring out AI's preferred ways of functioning—support its acceptance. However, these results do not address, e.g., the possible effects of use context(s). Also, while the importance of reciprocal interaction in building user trust and understanding is acknowledged, it is not addressed in terms of, e.g., effort expectancy (Gursoy et al. 2019).

2.3 Citizens' role in relation to smart city services

HABIB et al. (2020) and Kuberkar (2020) suggest that citizens need to feel capable of using Smart City services to accept them. An important factor is prior experience in using technologies that are perceived as similar to those of the Smart City. This is akin to Yeh's (2017) description of personal innovativeness, i.e., the ability to accept and

understand the characteristics of Smart City services that are based on information and communication technologies (ICT). Aptly, technology anxiety is commonly used as a measure for predicting citizens' willingness to use anything AI-powered (Lytras et al. 2021).

Sengboon et al. (2018) identified the ideal Smart Citizen as someone who is active, independent, aware, educated, and participates in public life. This entails a notion where personal attributes can define, at least to an extent, what type of people are up to par users for Smart City services. This view is corroborated by Cowley et al. (2018). They note that “the Smart Citizen” is only allowed certain modalities to identify with such as *service user*, i.e., consumer of services, *entrepreneurial*, i.e., actively enrolled into co-creating and innovating, and *civic*, i.e., taking part in grassroots activities. In similar fashion, a service is more likely to be accepted if the beneficiaries belong to a group of people that are deemed “deserving”, such as the elderly (Lytras et al. 2019). Additionally, demographic or personal characteristics such as age, education level or domain-specific knowledge contribute to the attitude toward AI-based services (Araujo et al. 2020; Zhang and Dafoe 2019).

Kerr et al. (2020) note that AI-powered automation and efficiency are depicted simultaneously as the most negative and the most positive aspects of AI. This can be explained by the role AI takes in relation to humans. Serving and helping humans are preferable to AI being interpreted as exerting control over them. Human experts are preferred to AI-based systems in application areas or tasks that require specialized skills, such as performing medical procedures. AI was defined in reference to humans, and it was assigned competencies, e.g., AI can support humans with simple and pre-programmed tasks (Alizadeh et al. 2021; Voda and Radu 2018).

Mou and Xu (2017) found differences in interaction preferences for human–AI and human–human communication. Interaction with AI-based services lacks socially desirable traits, such as agreeableness, extroversion, and openness. Still, if the AI system has “a personality” that appears similar to one's own personality, and it demonstrates enough social cues such as context awareness, it could be seen as worthy of social responses.

As a summary of the related work, we conclude that even though there are studies on citizens' preferences in relation to Smart City services, the in-depth understanding of user perceptions in everyday context is largely missing.

3 The survey: citizen AI impressions

First, we conducted a survey to gather initial citizen AI impressions to study them further in Smart City context in the interviews. The idea was to establish a basic

understanding of citizen impressions of AI and what it is. We carried out the survey at a science event, Tiedon valoa (Light of knowledge) in Tampere, Finland, in January 2020. The theme for the event was active citizen participation and the event was open to public.

3.1 Study design

The survey included examples of everyday AI, e.g., of recommendation algorithms, navigational and wellness solutions, digital marketing, and virtual assistants. These examples were chosen due to their expected familiarity and to raise discussion on everyday AI and citizens' awareness of it. The survey covered topics, such as citizen needs, concerns, and perceived benefits and risks of AI and Smart City solutions.

Due to the nature of the event, the survey was designed to be short, consisting of 12 questions. Five of these were multiple choice. The distinction between urban AI and AI in general was not explicated to the respondents to avoid possible confusion. The focus of the survey (Smart City solutions) was deemed as a sufficient contextual cue. The survey was circulated among the visitors on a tablet. We collected 91 responses from citizens aged 19–73. The average age of the respondents was approximately 39, with standard deviation of 12.5 years. The answers to open-ended questions were analyzed by thematically grouping individual replies. The number of occurrences of perceptions from the multiple-choice questions were summarized.

3.2 Survey results

Most of the respondents (88) were relatively familiar with the term AI. The open-ended question “What do you think AI means?” was approached from three different perspectives: 1. from a technical viewpoint, e.g., AI is an algorithm, 2. from a viewpoint that focused on the uses for AI, and 3. AI's impact on one's own life. AI was depicted as something that copies human activities. One-fifth understood AI as something that is manmade, whereas the rest considered AI to be a separate entity with a “mind” of its own and its own ways of working. AI was commonly referred to as a robot or a machine. One fourth saw AI as something that is meant to help people and the society.

Most of the respondents described themselves as either active, mainstream or a forerunner follower of technological development, and attitudes toward AI were mostly positive: curious (33), hopeful (29), or excited (26). This might be explained, at least in part, by the nature of the event. Most of the respondents (79) saw time-saving features as the main expected AI benefit, and AI was assumed to improve, e.g., well-being (71), work efficiency (67), safety (66), and carbon neutrality in buildings (66). When asked about the perceived

threats of AI, common concerns were possible decrease of humanness (65), loss of human contacts (63), and privacy issues (63). Also, fear of using AI, e.g., for military purposes was mentioned (26).

The respondents discussed AI benefits and concerns mostly on a societal level, not in personal use. The results confirmed the need to define AI in a more concrete way, in real-life context to gain a better understanding of the citizens AI perceptions. Thus, we used these survey results as background information for designing the scenarios for the interviews.

4 The interviews: citizen perceptions of AI in the smart city context

In the second part of the study, seven in-depth interviews were conducted to form a more comprehensive picture of citizens AI perceptions, focusing on what they deemed as desired and undesired attributes of AI. The interviews were conducted between July and October 2020. The interviewees were 25–71 years of age. They were city residents of Tampere, Finland that has an on-going smart city program. Interviewees were intentionally selected to represent varied backgrounds. The participants were: 1. female, 44, programmer, 2. male, 53, shop manager, 3. male, 37, process operator, 4. female, 42, journalist, 5. female, 71, retired psychologist, 6. female, 31, art restorer, and 7. female, 25, physics coach. No prior experience of AI was expected. The interviews were held remotely in Teams (4) or via phone (3) and recorded. The average duration for an interview was 1 h.

4.1 Study design

Six central AI themes based on HCAI literature were used as a basis for the interviews. The themes were: 1. Sense of control, 2. Sense of trust, 3. AI autonomy and initiative taking, 4. Privacy and data ethics, 5. Understandability, and 6. Suitability to a given task. These themes were written into five fictitious scenarios that focused on relevant smart city topics. The pre-study survey revealed the need to define AI in a more concrete way, in real-life context to gain a better understanding of the citizens AI perceptions. The pre-study provided information on the desired and undesired AI attributes, concerns related to privacy, and the interest in time-saving features, and carbon neutrality in buildings.

The topics were selected to cover a wide range of potential AI use contexts to ensure that the participants could relate to them. Scenarios were utilized to stimulate discussion, provoke thoughts, and to provide a concrete framework to think within (Rosson and Carroll 2009). The scenarios illustrated the uses and functionalities of different types of AI solutions in everyday context: how, where,

and for what a certain AI solution could be used. Thus, the interviewees were asked to imagine themselves amid the stories presented in the scenarios.

The scenarios were sent to the participants in advance to give them time to familiarize themselves with the topics. They could choose freely which scenarios they wanted to discuss. A minimum of two scenarios were required. The scenarios were intentionally left open-ended to allow the interviewees to complete the story in a way that would describe a desirable process or outcome. The aim was to get the interviewees to identify and express things that might impair or benefit their overall user experience. The scenarios that were discussed in the interviews were as follows.

4.1.1 Scenario 1: personal AI assistant

This scenario focused on proactive suggestions through voice UI. It depicted highly personal use of AI, covering topics of smart home and smart mobility. Four out of seven interviewees chose to discuss this scenario.

“It’s a busy weekday morning. The voice assistant on your device reminds you that you have a meeting first thing at work. The meeting is at a client’s and according to the email that just arrived the meeting has been postponed by 15 minutes. You have a bus arriving at your stop at 8.50. At the same time, the assistant reminds you that there’s a chance of rain—You must take the umbrella! Because you have a bit of extra time, the app suggests...”

4.1.2 Scenario 2: smart traffic stop

This scenario introduced a smart traffic stop, utilizing a shared smart screen. It combined public space and a mobile application in personal use. It addressed smart mobility, human identification, people flow analysis, and targeted, personalized content. Three out of seven interviewees chose this scenario.

“You’re waiting for a bus at the stop. The screen of the smart stop scans the people waiting and displays targeted content: this time it’s culture news. They seem relevant, at least to you. After all, you have edited your preferences in your own, personal mobile app. Suddenly the screen at the smart stop starts to blink. It says that there’s an unexpected traffic jam on the route of your bus. You take a look at your phone, and it shows you an alternative route for avoiding the jam. The app also lets you know that there are city bikes available in the nearby park, in addition to that...”

4.1.3 Scenario 3: feedback chatbot

This scenario focused on customer service, information sharing, and citizen participation through a mobile app. It addressed privacy issues, location tracking, and security. Four out of seven interviewees chose this scenario.

“It’s a winter’s evening and you’re on your way to the grocer’s. It’s dangerously icy, slippery and you’re a bit annoyed by the poor gritting. In addition to that, some of the streetlights are out. You decide to give the city’s new feedback channel, the feedback chatbot, a try. In the Feedback-chatbot app on your mobile, the bot greets you and enquires if you’ll allow saving your location data or if you’d like to add that information manually. It also asks if you want to receive a notification when your feedback has been received. It’s cold and your fingers are beginning to freeze. You tell the bot your concerns about the gritting and lighting, and the bot displays what you have said in text and confirms that it has understood you correctly. Later...”

4.1.4 Scenario 4. Sustainable office buildings

Scenario 4 introduced a topic of carbon-neutral public buildings in a smart city. It depicted how motion sensors and real-time information tracking could be utilized. None of the participants chose this scenario, although in the survey, the respondents showed strong interest in this topic.

4.1.5 Scenario 5. Emotion tracking AI

This scenario focused on the citizen well-being and urban culture through an AI art object. It envisioned emotion tracking and facial recognition in public space. This was the most popular scenario among the participants; six out of seven interviewees chose to discuss this.

“It’s a summer’s day and you’re walking in a park admiring the flower beds. You stop in front of a new interactive artwork. The artwork recognizes your mood based on your expression –happy– and changes color from blue to bright orange. There’s a display next to the artwork where you can see people’s moods: It looks like yellow is the dominant color today. From this you can conclude that...”

The interviews were analyzed following the six central steps of thematic analysis presented by Braun and Clarke (2006). The transcribed data corpus—the whole data—was first coded based on the six predetermined AI themes to get an overall view of their occurrence in the data. The second step was more inductive, focusing on how the broader and

somewhat nebulous AI themes were concretely discussed. This allowed us to map the underlying factors reflecting the dimensions that contributed to the interviewees thinking and latent, not immediately detectable themes to be formed. For this, we utilized a visual collaboration Miro board (miro.com) to enable teamwork to further elaborate on the themes. After the five central themes were identified and labeled, they were examined in relation to the scenarios. How did these themes arise in the contexts presented in each scenario and in what way? Our approach can thus be described as constructionist in that the aim was to go beyond what seemed apparent, the general thinking patterns, and capture practical indications for everyday AI design.

4.2 Results: underlying views of AI use in smart cities

Recurrent general AI perception themes were labeled based on the underlying views and attitudes toward the use of AI. Each scenario highlighted different aspects of these main themes, illustrating concrete and contextually relevant expectations and preconditions. The focus was thus on the possible requirements informing everyday AI design.

4.2.1 “I don’t like *them* monitoring me”

This attitude illustrates the need to maintain what is deemed as one’s basic right for privacy, for not being ‘watched’ all the time, everywhere (Caluya, 2010). This thinking acknowledges an uneven distribution of power and emphasizes the need to feel in control and to set boundaries according to one’s preferences. In addition to these already well-reported qualms concerning the ubiquitous and deliberate nature of data gathering, privacy issues were brought up in specific contexts. The use of voice-based UI (user interface) in Scenario 1 evoked misgivings. The interviewees felt that the personal assistant might interfere where it is not allowed, possibly disrupting personal routines that were key to ensuring busy weekday mornings remain smooth and efficient. They considered using voice, in particular natural speech, attention demanding, and authority seeking (*female 31, female 44, male 53*). AI taking initiative in social settings was depicted as problematic. The participants assumed AI applications to lack ‘social finesse’ and context awareness. As a result, they expressed concern that the assistant could reveal something private in the company of other people via the voice UI:

“In real life, I’d prefer a “ping”. I’m pretty careful with my privacy when it comes to situations where other people are present. If it would remind me to go there, to do that, I’d feel exposed.” (Female 31).

The same concern related to the smart stop (targeted content, shared screen). AI made the final choice what to display on the screen based on predetermined user interests. This became problematic if there were only two people at the stop or a lot of people with a common interest that was very different from one’s own. As it was unclear what AI would display, feelings of uncertainty and apprehension were evoked. How would the others at the stop react? Is this an interest I would like to share with people I don’t know (*female 31 & male 37*)? With the feedback chatbot, it was unclear whether the bot could initiate interaction. Though the possibility of the bot “*randomly hollering from the pocket*” (*male, 37*) was met with amusement, it was not desirable. This could draw unwanted attention to the user and remove the opportunity of “going incognito” that was seen as essential to wandering about the city.

The emotion detecting artwork highlighted privacy issues related to the thought of being singled out. There were two simultaneous expectations: 1. to see the interpretation of one’s emotional state and 2. the others present not seeing it. One’s emotional state was considered private information. All participants were eager to test the artwork’s ability to detect their personal emotional state. They wanted to see if they agreed with the “reading” and whether they could influence it by changing places and expressions. This raised questions about the integrity of the artwork. That is, the data gathered from passers-by can be misleading and untrue (*female, 31, female 42, and female 71*). The normalization of data gathering was also discussed: could applying AI in this manner normalize more extensive data collection in urban environments?

4.2.2 “I want maximum gain for minimum effort”

This perspective depicts an instrumentalist and teleological view toward AI. While people were keen to benefit from personalization, the amount of time and effort they were willing to invest in “actively teaching” AI was minimal. Still, personally relevant and useful results were expected consistently. In Scenarios 1, 2, and 3, this was showcased by listing personal requirements that would presume AI to act with a situational awareness unattainable to most humans.

The interviewees appreciated the possibility to report a problem quickly on the spot, via a clear channel (feedback chatbot), by speaking. Another key feature was receiving feedback via the same channel. The feedback ensured that the users’ input was acknowledged and rewarded by providing information on the progress (without further effort). The feedback did not need to be personal as that was deemed possibly taxing. That is, the reported problems were not personal enough to allow, e.g., multiple notifications. Still, the perceived practicality and ease of use contributed to another form of avoidance. If the feedback bot became widely used,

the user would not need to bother to report anything as someone else would surely go through the trouble (*female 25*).

In Scenario 5, the possible gains and efforts were reframed. The interviewees were intrigued by the artwork and expressed a willingness to interact with it. The gain was thus the action itself, having fun, and seeing the outcome. Also, the application did not require the users to do anything, all “effort” was voluntary (*female 44*).

4.2.3 “I don’t want AI to mimic people”

This attitude deals with the style AI operates, especially in contrast with human behavior. On the one hand, this reflects on the perplexity AI can cause by imitating humans, i.e., operating in a way that indicates social agency akin that of a person. On the other, this includes the understanding of people as biased and prejudiced. AI is thus seen as one possible means of overcoming human shortcomings, exceeding our abilities. In essence, the interviewees depicted AI either as inferior to humans or superior to them—not as an equal. This implies that the attributes AI displays cannot be equal to those of a human.

The interviewees described the personal assistant as an optimizing machine that should understand humans sufficiently well to deliver relevant outcomes. The ideal way for the application to interact was distinctly devoid of any inconsistencies that are typical of interpersonal communication. The feedback chatbot enabled smooth reporting of a problem and allowed the user to avoid “talking to people” or finding the right people to talk to (*male 37, female 42, female 71*). The application solved the problem of unnecessary communication and saved the user time and trouble. Still, the way the bot operated (greeting, confirming that it had understood what the user had said) was met with apprehension (*female 42*). The bot was not seen as competent social agent, and thus, it did not have authority to claim it had “understood” what had been said. It is the user who confirms that the bot’s interpretation was acceptable. Also, greeting the user out loud, repetitively, was seen as an unnecessary step in the interaction: “*The bot is in no need of social courtesies, and neither am I. It’s a bot.*” (*Female 42*). In this scenario, the work the bot did (receiving notices) was not deemed as actual work. The actual work (allocating tasks to right people, fixing what needed to be fixed) was done by people. Essentially, what people do is work, what AI does is considered as something else.

The interviewees doubted that the personal application linked to the Smart City stop screen would understand what kind of content is appropriate to share. It might display information that is private or unsuited for a situation where other people are present. Thus, not being able to protect the user from possible harm that might ensue. This

contradicts the totality of the view of AI displaying any human qualities. Still, it maintains the view of AI being here to support our needs, whatever they may be. In this scenario, AI was also expected to be able to offer users something new based on their interest or needs (*female 31, female 25*). That is, to go beyond one’s imagination in a relevant and interesting manner. This was evident in testing the artwork. It was assumed that the user could fool the machine, outsmart it. This would confirm that human emotions are too complex and nuanced for AI to fathom, i.e., reinforcing the view of humans as superior to and different from AI. In consequence, this could intensify mistrust in AI.

4.2.4 “I’ll avoid using AI if I consider the risk too high”

This perspective refers to AI use where the user is present, but not directly in control. The more serious the possible imagined consequences or the strain for the users are, the greater is the need for risk aversion. On everyday level, this perspective is illustrated by “the safeguarding techniques” the interviewees suggested or assumed to be in place. Minor inconveniences, such as unwanted interruptions, could be avoided by limiting or fully preventing AI from taking any initiative that can directly be seen or heard (personal assistant, smart traffic stop, and feedback chatbot). This relates to AI applications that are in personal use containing private data. In scenario five, the premise is communal. The visualized data are gathered from all, not from anyone particularly. This evoked a sense of anonymity and security, as in that context and setting, individuals and their emotional states were not “exposed”. While applications that required detailed personal information, e.g., health-related data, were deemed risky, this could be overcome by having a choice. That is, the user could choose to use a particular application (*female 44*). Additionally, having choices within the application that related to issues the users deemed important (e.g., sharing location data) and that these choices were presented timely and in relation to what the users were trying to do, made the possible risks seem manageable.

The interviewees depicted cognitive load and effort as risks. AI was given an assistive, supportive role and its priority was to reduce human workload. AI applications would need to have a way (outside detectable, active user involvement) to prioritize and categorize information according to user needs, automatically. In the risk aversion context, self-driving cars were depicted as an example of a worst-case scenario. The risk to human life, even if not probable, was considered too high. It was the human passenger who would have to live with the possible consequences, left wondering could he have done something to prevent, e.g., a crash if he’d had control (*male 37*).

4.2.5 “I don’t need to be concerned about AI”

This perspective describes a view that AI is essentially just another technology that people—in time—will get used to. AI’s appropriate operation is taken care of by the developers and by any service provider who chooses to utilize AI. This depicts a way of thinking where responsibility is not placed on any single individual, but rather on a group of experts (such as engineers) that is deemed sufficiently trustworthy. AI was seen as a part of the “natural” and familiar trend of technological advancement and digitalization and was thus depicted generally quite harmless. If the users had not experienced any unpleasant consequences personally, all was assumed to be in order.

Also, the application checking if the user wanted to share sensitive data assuaged worries (feedback chatbot). The acceptance of the use of AI was discussed also in terms of personal attributes. An ideal AI user would have sufficient technical aptitude, curious attitude, and would be of a certain age (*male 37, female 25*). There were thus people that were, due to lacking these qualities, overly worried. Considering the artwork, the participants assumed that someone (the city, municipality) had made sure that the artwork functions within the boundaries of current legislation (*female 42*). On the other hand, it was seen as possible commentary on the risks of AI, thus making them more visible to general public (*female 31*).

The interviewees saw no reason the fret over something that—in time—would become a natural part of citizens’ lives. The younger generations would deem current worries as unintelligible, having grown up in a society where the use of AI was the norm (*female 25*). However, the interviewees assumed that it would still take a long time “another 50 years” (*female 44*) before AI was mature enough to function on level that is notable enough to bring about significant, concrete changes in citizens’ everyday lives.

5 Discussion and conclusion

The results highlight several desirable and undesirable attributes for AI-powered, everyday Smart City services. First, we reflect on our main findings on acceptance factors in relation to previous research. Second, we elaborate on our methodological choices and possibilities for future work.

5.1 Reflections on the main results

The “**I don’t like them monitoring me**” theme highlights the importance of the way AI “behaves” and displays information. AI-systems’ ability to read social situations was questioned. Thus, to be accepted, they should not be allowed to initiate interaction in a way that attracts untoward

attention or reactions from bystanders, to autonomously decide what information to disclose nor automatically disclose information in the presence of others. This specifies the requirement Meurisch et al. (2020) and Koelle et al. (2019) pose for adjusting the system’s level of proactivity and preserving the user’s sense of control. Utilizing voice-based UI, especially natural speech, is deemed problematic as it can be interpreted as “demanding”. Whether this is affected by linguistic elements such as politeness suggested by Ischen et al. (2020) or other factors such as aversion to sound cues, inexperience or cognitive dissonance (e.g., AI trying to establish itself as a worthy social agent) requires further investigation. In similar vein, the characterization for AI-system implementation can cause ambivalence: the artwork in scenario five was considered enticing, but it could also be interpreted as an instrument for normalizing more extensive data gathering in urban environments. That is, as an attempt to manipulate public opinion (Zhang and Dafoe 2019). The application area, emotion detection, was also questioned. This relates to the competencies AI-systems are believed to have and how these beliefs can affect accepting system outputs. How could a machine that has no emotions recognize human emotions? This is parallel to Voda and Radu’s (2018) and Alizadeh et al.’s (2021) findings: some skills are considered distinctly human. Emotions and emotion recognition seem to belong to that category.

The “**I want maximum gain for minimum effort**” theme reveals the expectation for AI-based services to meet users’ personal needs and requirements, preferably automatically. In public services (such as the feedback bot) that require some level of activity on the citizens’ part, this effort needs to be acknowledged and rewarded by sufficient feedback. This type of voluntary and active citizen participation fits the description of the ideal Smart Citizen by Sengboon et al. (2018). Reciprocal interaction can reinforce citizens’ trust in a service if the interaction is deemed personally useful and effortless (Ischen et al. 2020; San Martín et al. 2020; Zhang et al. 2020). Still, our findings highlight the need to consider the character of a service as it can affect the amount and type of reciprocal interaction that is deemed worth the effort. The preferred way for a service that has a clear purpose—such as reporting specific issues—to function is to categorize reported issues based on, e.g., their urgency and to delegate them forward automatically, without further user input. Kerr et al. (2020) propose that these types of AI-based support systems are well received. The interviewees concurred. They appreciated the efficiency and found it preferable to having to give a wordy account to a human recipient. However, if a service such as the feedback bot became widely used, the need to engage personally could diminish. If the aim of the service is communal, the responsibility is shared. Lytras et al. (2019) note that services that promote communal activity for common good are generally well accepted. Still, there

are factors that can influence users' willingness to continue their use. In leisurely context, including gamification or novel elements can encourage active engagement with a service: the user activity itself or any following outcome that relates to the user personally can be seen as rewarding.

As Mo and Xu (2017) suggest, interaction with AI is expected to be straightforward and goal-oriented, devoid of the diversity that typifies interpersonal communication. This type of interaction with AI-based services was seen ideal in clearly defined, uncomplicated matters. Another aspect of **"I don't want AI to mimic people"** relates to cognitive qualities. AI using expressions such as "I understand" is seen false, as understanding is seen as a human trait, requiring human cognition. In addition to highlighting the distinction between human and AI abilities, this specifies the need to consider linguistic elements (Ischen et al. 2020; Kerr et al. 2020). Based on our results, it is not enough to consider just, e.g., the tone, the wording needs to be considered as well. The attempts to conceal AI in this manner can result in counterproductive outcomes, as any oddness in human–AI interaction can lead to mistrust and discontinued use (Shneiderman 2020; Zhang et al. 2020; Duffy and Zawieska 2012). While AI is depicted as lacking human qualities, it is expected to acknowledge them and to apply that information for the user's benefit. (Ford, 2015). Still, citizens can be curious about AI's human-like abilities. If these abilities are deemed insufficient, the differences between AI and people might be emphasized. This can lead to doubting AI and its ability to provide meaningful assistance. AI is also expected to exceed user expectations, to provide something new and relevant based on already known user needs and interests. This is congruent with the findings of Ji et al. (2021) and Sepasgozar et al. (2019): citizens are inclined to accept Smart City services that can enhance the quality of their everyday life and offer relative advantages (in relation to the already available services).

"I'll avoid using AI if I consider the risk too high" perspective underlines the fear of not having or losing control and weighing the perceived benefits against the possible risks. As Habib et al. (2020) phrase it: the costs of a service should not exceed its benefits. According to Kocielnik et al. (2019), being able to directly impact the system is essential for the user to establish a sense of control. The interviewees perceived making choices as an important way to "impact the system". If they had personally chosen to use a service and were able to make choices within that service according to their preferences, their sense of control was strengthened, while the possible risks became manageable. Thus, the interviewees saw sense of control as essential for assuaging worries. From the perspective of personal use, cognitive load and effort were depicted as risks. Providing information for or "teaching" AI applications to allow personalization was seen as arduous and thus as "a risk" for their acceptance and

use. This can be described via the effect of effort expectancy (Gursoy et al. 2019). AI could support users by gathering the required personal information for its own use automatically. Previous research did not address risk from this perspective. Also, risks that were deemed communal (such as data gathering from online behavior) were felt less personally. Being part of a larger group created a sense of relative anonymity and unimportance of one's personal information. Safety is in numbers.

"I don't need to be concerned about AI" theme depicts AI development as a natural part of the already familiar digitalization process of Smart Cities. The view of AI as problematic is associated with groups of people that do not possess the necessary skills (such as technical aptitude) or personal characteristics (such as open-mindedness) to accept or utilize Smart City services. The interviewees did not question this disposition. That is, it was deemed natural that all citizens are not equally able "Smart Citizens". This confirms Sengboon et al.'s (2018) findings related to the aware, independent, and active ideal Smart Citizen. This can pose inclusivity problems that relate to people's attitudes toward one another, not directly to the use of AI. Even so, the citizens that have "limited abilities" to accept and utilize AI-based Smart City services can still be seen as worthy beneficiaries. As Lytras et al. (2019) attest, the elderly, for example, were seen as a deserving group of people. Furthermore, AI is seen as "a work in progress". There is time for people to adapt to AI and for the current concerns to become obsolete. Citizens are depicted as a varied group of individuals that cannot be held responsible for the way AI generally operates and what it is utilized for. Accountability and responsibility are thus placed on AI experts or service providers. This is in line with Zhang and Dafoe (2019) and Sepasgozar et al.'s (2019) views. However, Shneiderman (2020) would encourage citizens to take responsibility for any AI applications' actions they use. This could strengthen their sense of control and trust in their own abilities thus encouraging continued use.

5.2 Methodological considerations and future work

AI is an abstract subject, and the interviewees were not expected to be familiar with AI-based Smart City services. Thus, we chose to utilize scenario-based interviews to elicit current citizen views about AI-powered Smart City services. Still, we acknowledge that there are alternative approaches that can capture concrete user behavior and could provide valuable, additional insights. Utilizing prototypes, collecting and analyzing log data, experimenting with an existing AI application for a period and reporting perceptions based on a more systematic use are some examples.

Though our pre-study did not bring forward novel insights, it confirmed previous results and their local

relevance (Fagbola and Thakur 2019; Habib et al. 2020; Ji et al. 2021; Kerr et al. 2020). The survey also provided background information for planning the scenarios for the interviews. Scenarios proved to be a viable method for demonstrating the use of AI-based services in a way that allowed the interviewees to recognize and discuss AI-related functions and features in a concrete way. However, the task where the participants were asked to continue the story in the open-ended scenarios did not provide any significant additional data. The answers were short and depicted outcomes that were based on the possibilities that were already present in the scenarios. Still, this can be interpreted as a sign of successful scenario design: the examples were defined concretely and clearly enough to be unambiguous. Another possible explanation is that people without AI background or any significant practical experience of AI-based services are not that eager or able to envision possible uses of AI.

Both the data from the pre-study and the interviews have limitations. The pre-study was conducted at an event that was themed “Smart City solutions”. It is reasonable to assume that the visitors had a pre-existing interest. As for the interviews, there were only seven and the findings are on no account generalizable. Still, the qualitative data are quite rich and brought up versatile perspectives. All the five general AI perception themes were present in all interviews. The individual views and preferences the interviewees presented in relation to the scenarios varied. Although this was to be expected, the importance of these individual views and preferences could be further validated by collecting a broader data set for example by a survey.

In addition, while the interviewees were chosen to represent varied backgrounds, that only applies to their age and profession. All were employed (one of the participants was already retired), seemingly middle class, active, and had some experience with technology. In that, our study can be seen as reproducing the stereotype of “the ideal smart citizen” (Sengboon et al. 2018). In addition, the role our interviewees were given was that of a service user, i.e., consumer (Cowley et al. 2018). While that seems fitting, it can also narrow the interviewees’ perspective and reasoning (Cardullo and Kitchin 2018).

Future research could benefit from historical perspective. Building an understanding that is based on the evolution of user perceptions on AI-based services could validate and illuminate important aspects. It could also be worthwhile to consider possible culture-specific inclinations. Additionally, as the user perceptions reveal a myriad of needs, preferences et cetera, it could be useful to try to determine their respective relevance for accepting Smart City services. That is, to find out what needs to be prioritized.

On a more practical level, different Smart City stakeholders need to be included in the discussion about people’s needs for AI-based Smart City services. Concrete

application design and deployment cases can be developed and studied to define domain-specific perceptions of AI. Such insights could be formulated to design guidelines and tools that can provide systematic and operationalized support for AI application design.

6 Conclusion

The goal of this study was to explore citizens’ perceptions of AI-based Smart City services in the context of personal, everyday use. Our results suggest that, in that context, aspects such as being aware of what kind of abilities and behaviors are deemed distinctly human, the importance of social norms for the acceptable use of, e.g., proactive systems, factors the users can deem as risks, and the expectation that, e.g., the service providers take full responsibility for the safety and security of their services, can affect citizens’ perceptions and attitudes. Our findings can thus be seen as recommendations of human-centered factors to consider while designing acceptable AI-powered Smart City services.

Data availability The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

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