AI & SOCIETY
https://doi.org/10.1007/s00146-025-02815-8

REVIEW

Unfamiliar but desired: citizens' attitudes toward smart city applications

Daria Szafran[1,2] · Ruben L. Bach[1]

Received: 20 October 2025 / Accepted: 12 December 2025

Abstract

Urban administrations increasingly rely on AI and data-driven solutions to address complex societal problems, such as climate change and the distribution of limited resources. Since the 2000s, the term smart city has been used to describe cities that use data and technology to foster efficiency, environmental sustainability, and citizens' quality of life. Although marketed as a promising way to a digital and data-driven future, numerous examples in recent years show that technology-based solutions may come with unintended and undesired side effects, e.g., excluding certain groups of people from access to resources. This may result in discrimination and increased social inequalities. While computer science and engineering research has been very active in developing smart city technologies, much less is known about the public's attitudes towards such technologies and whether these attitudes vary across different social groups.

To address this gap, we conducted a survey study (N = 2021) on public attitudes towards various smart city applications in May 2023 in a high-quality probability-based online panel in Germany. We presented respondents with eleven smart city technologies across four domains: mobility, social inclusion, public safety, and energy supply. Respondents indicated whether they are familiar with them and how much they would like to see the applications implemented in their neighbourhood. Using latent class analysis, we identified patterns of familiarity and desirability, and examined how these relate to gender, age, education, mobility impairment, migration background, income, and urbanicity.

Our analysis reveals distinct attitude profiles towards smart city technologies, with certain socio-demographic characteristics associated with different degrees of familiarity and desirability. The study makes a twofold contribution to the research on citizens' views on smart city applications: first, it offers a social science perspective that focuses on inequalities in public attitudes. Second, it complements the predominantly qualitative, small-sample literature with a quantitative analysis using a high-quality probability-based sample of the German population.

Keywords Smart city · Attitudes · Latent class analysis · Social inequality · Digital divide

1 Introduction

We live in turbulent times. While issues such as the environmental crisis and the persistent social inequality are certainly not new, their scale and impact demand concrete efforts to find solutions for a sustainable and livable future. As densely populated areas, cities contribute considerably to crises due to extensive resource consumption (Albino et al. 2015). As a response, urban administrations worldwide increasingly rely on data-driven and digital solutions, often backed by artificial intelligence, that collectively fall under the term *smart city*.

Designed to allocate resources efficiently and sustainably as well as improve the quality of life of urban residents (James et al. 2020), smart city solutions cover an array of applications. Examples range from vehicle cameras detecting traffic violations (Rathore et al. 2021) to systems managing water infrastructure (Oberascher et al. 2022) and e-government tools that enable automation in the provision of public services (Engin and Treleaven 2019; Shadowen et al. 2020). Although the deployment of these applications is not

✉ Daria Szafran
daria.szafran@uni-mannheim.de

Ruben L. Bach
r.bach@uni-mannheim.de

[1] Mannheim Centre for European Social Research, Mannheim, Germany

[2] School of Social Sciences, University of Mannheim, Mannheim, Germany

Published online: 23 December 2025

spread equally across cities, studies suggest that numerous metropolitan areas pursue some version of a "smart city strategy" (Angelidou 2017; Golubchikov and Thornbush 2020; Joss et al. 2019).

Despite the promising narratives surrounding the implementation of smart city applications (Joss et al. 2019; Sadowski and Bendor 2019), there are also legitimate skeptical reactions. Apart from the critique of the ideological nature of the term "smart city" (Cugurullo 2018), which begs the rhetorical question of "who wants to live in a dumb city" (Lindner and Meissner 2018:10), critical scholars argue that the smart city agenda is mainly driven by private tech companies that view lived spaces as exploitable markets (Kitchin et al. 2019; Vanolo 2014). Recent research demonstrates smart cities' potential to reproduce existing social inequalities: Maalsen et al. (2023:299) reveal that the smart urban transformation is highly gendered, with primarily men being involved in the planning and design of the technologies, which might result "in 'smart cities' designed for men." Further, Kaharevic and Wihlborg's (2024) review shows that the perspectives and needs of residents from disadvantaged neighbourhoods are often omitted in the implementation of smart cities.

As a multifaceted concept, the smart city lies at the intersection of technology, governance, urban planning, and environmental sustainability. This explains why it attracts various academic disciplines (van Twist et al. 2023). Although valuable, those perspectives seldom consider the public's view on smart cities. Ultimately, however, this stakeholder group will be most exposed to smart city applications and their implications, as the technologies are primarily embedded in citizens' living environments. In light of the aforementioned examples of how smart cities can reproduce social inequality, it is essential to examine how citizens view the technologies.

Previous research on smart cities that takes a citizen-centric approach consists primarily of case studies focusing on individual applications. While being based on small samples and applying qualitative methods (van Twist et al. 2023), they do not allow for the generalization of findings. In fact, recent reviews of the research field highlight the lack of quantitative studies (Echebarria et al. 2021; van Twist et al. 2023) that should complement existing literature by revealing potential differences in attitudes towards smart cities between various social groups. To address this call, we aim to answer the following research question: *What distinct patterns underlie public attitudes toward smart city applications, and how do individuals' characteristics shape these patterns?*

We do so by analyzing data from a German probability-based online panel, which surveyed 2021 respondents regarding their attitudes towards eleven smart city applications related to mobility, public safety, energy supply, and social inclusion. In our study, we adopted an exploratory approach and investigated the extent to which the familiarity with the applications and the desire for their implementation vary depending on the application. Further, we explored whether there are differences between societal subgroups concerning these two aspects. Our findings offer researchers a nuanced understanding of citizens' attitudes toward smart cities and highlight the characteristics along which disparities may arise. They also provide practical insights for smart city designers and planners by presenting a differentiated picture of citizens' preferences based on various real-life applications.

The remainder of this paper is structured as follows: In Section 2, we present the theoretical motivation for this study and review previous literature on smart cities focusing on citizens' perceptions and attitudes; in Sections 3 and 4, we describe the data and our methodological approach before we present the results in Section 5; in Sections 6 and 7, we discuss the results and address the limitations of our study; in Section 8, we conclude our findings.

2 Background and related literature

2.1 Theoretical motivation

A critical approach towards the implications and consequences of smart cities is driven by the vision they promote and the urban spaces in which they are embedded. At the core of the argument is the premise that smart cities, like all technologies, do not emerge organically, but are socially and politically constructed (Bijker 2010; Winner 2007). Thus, a comprehensive understanding of technologies requires the consideration of the social and political context in which technologies are designed and deployed.

Since the mid-20th century, computer technologies have been used in city administration, e.g., to store data, model behavioral patterns, or provide various services (Batty 2024). As such, the idea behind the smart city has historically emerged from the notion of a digital, connected, and technocratic city that existed before the term gained popularity (Kitchin et al. 2019; Shelton et al. 2015). Although the concept remains fuzzy in terms of its definition (Albino et al. 2015), the smart city can be described as "seek[ing] to improve city life through the application of digital technologies to the management and delivery of city services and infrastructures and solving urban issues" (Kitchin et al. 2019:2).

The smart city emerged as a global agenda for cities in the 2000s. This was primarily triggered by the economic crisis at the time, which forced actors in the private and public sectors to adjust accordingly. Consequently, the *smart city* reflects how the drive of tech corporations to tap into new markets aligns with urban governments operating under austerity politics. Considering the larger context, this integration has been further facilitated by the (late) capitalist trend towards increasing privatization of urban areas and services. For a more detailed description, see Kitchin et al. (2019).

Alongside this development, critical research has questioned the extent to which smart cities impose a neoliberal logic in redefining the city itself, its governance, and the role of its inhabitants. Vanolo (2014) coined the term *smart-mentality* to characterize this transformation. Drawing on Foucault's concept of governmentality, he describes smart-mentality as a new "urban identity" that simultaneously functions as a "discipline mechanism" for cities. Accordingly, cities become *products* whose performance can be measured against benchmarks and evaluated depending on how well they adhere to the smart city agenda. This allows a classification of cities into either "good" or "bad," suggesting that the latter are "smart-deviant." Vanolo (2014) further argues that the smart city agenda seeks to appear politically neutral, although its objectives and the means of achieving them are politically constructed. Beneath the guise of the smart city lies a neoliberal policy that aims at a technocratic transformation of power relations to make the city attractive primarily for its wealthier beneficiaries, i.e., investors, tourists, and highly skilled professionals, largely omitting the voices of urban residents.

Regarding urban residents, Vanolo (2014) argues that the production of smart cities inherently entails the co-production of "smart citizens." Just like the urban spaces themselves, residents are subject to the normative expectations imposed by the smart city agenda. Kitchin et al. (2019) describe the figure of the "smart citizen" as one shaped by specific expectations regarding how residents of smart cities should think and behave. The smart urban resident is thus constructed "as a data-point, a targeted consumer, a user, an investor, a sorted individual, and a surveilled, controlled and policed subject" (Kitchin et al. 2019:9). In line with neoliberal principles, citizens are ostensibly granted freedom of choice; however, it often proves illusory upon closer examination. Rather than being genuinely empowered, urban citizens are subject to constant, more or less subtle forms of monitoring and control. The predominant smart city narrative masks this surveillance by exploiting the positive connotations of the term *smart*, making it appear natural. This normalization of control and surveillance helps legitimize the broader political agenda underpinning the smart city vision. Moreover, this specific image of the smart citizen assumes a homogenous individual who fits into a rigid mold. Such a view overlooks the diversity of human experiences, ranging from differences in attitudes and personalities to the structural inequalities that shape individuals' lives. In particular, it fails to truly account for disparities related to gender, age, ethnicity, disability, income, and the inhabited *space* itself, as illustrated by the following examples.

McElroy and Vergerio (2022) show how "landlord tech," such as biometric facial recognition systems or smart access technologies, is being increasingly used to specifically surveil low-income tenants living in public housing complexes in New York. While often justified as security measures to prevent unwelcome individuals from entering the building, these technologies function in practice as tools of automated gentrification: they enable landlords to raise rents and evict poor and working-class tenants for lease violations. Due to the racism embedded in facial recognition algorithms, People of Color face a disproportionately higher risk of being falsely accused of committing such violations (McElroy and Vergerio 2022). Another example is Kintzi's (2024) ethnographic study of the smart energy transition in Amman, Jordan. It highlights stark disparities in the distribution of smart grid installations, such as in-home smart meters and rooftop solar panels, across 40 neighborhoods. The applications are concentrated in affluent suburban neighborhoods, while they are sparse or non-existent in areas that various refugee groups have historically inhabited. Kintzi (2024) compellingly demonstrates that this uneven distribution stems from asymmetrical power relations, manifested in the highly unequal land ownership. The study illustrates how real-world conditions constrain the smart city promise: smart infrastructure development is rooted in a long-standing (post)colonial legacy of land privatization. While a wealthy elite of property owners can install smart grid applications in the first place, families in poorer neighborhoods are sometimes completely excluded from the power grid. In addition, such technologies further exacerbate the prevailing unequal relations, as they enable the wealthy to access energy at significantly lower prices or even free of charge. In contrast, others remain indebted and dependent on energy distribution companies and their prices (Kintzi 2024).

These examples underscore that smart city technologies do not unfold in a vacuum but are shaped by, and actively shape, existing social, political, and economic inequalities. As the vision of the smart city continues to spread globally, it is essential to examine how different social groups engage with, benefit from, or are marginalized by this agenda. In this context, public attitudes and perceptions toward smart city technologies are not merely reflections of individual preferences but are embedded in broader power structures.

In the following section, we review existing research on citizens' attitudes toward smart cities, shedding light on how this stakeholder group understands, desires, or contests these technologies.

2.2 Research on public attitudes towards smart cities

Public attitudes towards smart cities have only recently gained attention in research (Spicer et al. 2023; van Twist et al. 2023). Van Twist et al. (2023) conducted a systematic literature review of 58 studies on citizens' discontent with smart cities, covering articles published between 2014 and 2021. The review explores the reasons behind critical attitudes toward smart cities, how citizens express their dissatisfaction, and how city administrations respond. It identifies two modes of citizens' discontent: *active* and *passive*. Active discontent is expressed through direct actions, which van Twist et al. (2023) categorize along two dimensions: individual versus collective and conventional vs unconventional. Conventional actions include, for example, posting concerns about smart city applications on social media (individual) or mobilizing activist movements that advocate for a societal rethinking of such technologies (collective). Unconventional expressions of dissatisfaction include deliberately covering cameras (individual) or engaging in data activism, such as hacking (collective). The authors identify three reasons driving an active expression of critical attitudes: i. discontent with the technological aspects of smart city applications (e.g., usability or design), ii. frustration due to a lack of participation opportunities, and iii. concerns about the negative societal impact of smart cities (e.g., privacy, digital divide, or surveillance).

In contrast to the active mode, passive discontent refers to the absence of visible criticism or opposition from citizens. It encompasses both a lack of critical attitudes towards smart cities from the public and the inability of dissatisfied citizens to express their sentiments. The former might be due to i. the invisibility of smart city technologies (e.g., sensors), ii. the absence of citizens' data literacy skills or interest in digital technologies and democratic processes, and iii. citizens' unawareness regarding the societal consequences of smart city technologies. The latter is tied to structural barriers, such as the dominant smart city narrative presenting the technological transformation as utopian and inevitable, the limited role of citizens in decision-making processes, and the exclusion of marginalized voices from the smart city discourse. Van Twist et al. (2023) emphasize that decision-makers should not interpret citizens' lack of active discontent as outright approval for the digital transformation. Within the smart city discourse, citizens' role is often reduced to mere users or testers of technologies. Instead, the authors argue that citizens must be recognized as political subjects with the right to participate in shaping the process.

Since 2021, additional studies have examined public perceptions of smart cities using survey data. Spicer et al. (2023) examined how smart city technologies match citizens' wishes and needs across four areas: services, governance, social, and the economy. The survey among 505 residents of three large Canadian cities shows that citizens' perceptions of "smartness" differ from the cities' actual smart city strategies, as citizens prioritize other areas than those targeted by city officials and stakeholders from private industry. Spicer et al. (2023) point out that this misalignment occurred despite cities' efforts to incorporate citizens' opinions. They conclude that key decision-makers should engage more with citizens and consider their perspectives. Previous efforts to engage the public may have focused too much on infrastructure projects and implementing new technologies, rather than on citizens' actual needs and concerns.

Further studies investigate the factors shaping public attitudes toward smart cities. Hartley (2024) surveyed 1017 Hong Kong citizens to examine whether awareness of smart city technology and perceived government transparency influence public support for smart cities. Support was operationalized using two variables: i. the extent to which citizens believe that Hong Kong should embrace the technological transformation and aspire to become a smart city, and ii. citizens' willingness to pay more taxes to provide smart city services. The results reveal that a greater awareness of smart city technologies and the feeling of being adequately informed about them lead to stronger civic support for smart city technologies. Building on this study, Hartley (2023) also focuses on drivers of public support. However, he operationalizes it as citizens' perceptions that smart cities can improve governance effectiveness and the quality of urban life. Again, awareness of smart city initiatives and the general belief that the government is responsible for its citizens' quality of life emerged as key predictors of public support. Hartley and Aldag (2024) extended this line of research by surveying 1500 residents of Singapore. They conceptualize public support as a multi-dimensional construct, distinguishing between i. *general support*, e.g., the willingness to pay taxes to finance smart city initiatives, and ii. *perceived effectiveness*, e.g., the belief that smart city technologies can improve urban infrastructure and governance. Their results identify several significant drivers of public support, including trust in technology, confidence about the security of individual data, and the belief that citizens' perspectives will be considered in the transformation process to a smart city. Awareness of smart city technologies and the overall belief that they improve the quality of life also positively influenced public support.

The reviewed studies provide valuable insights into citizens' attitudes toward smart city applications. While the literature suggests that awareness and trust play essential roles in shaping public support, the findings also point to discrepancies between citizens' preferences and municipal strategies that might be due to failed attempts to truly include the public in the process. Despite these contributions, further quantitative research on citizens' attitudes is needed, ideally from multiple perspectives and considering various aspects. Previous research utilizing survey data on smart cities mainly focused on identifying which (other) attitudinal variables correlate with attitudes towards smart cities. In these studies, sociodemographic characteristics such as age or education were primarily treated as control variables. Such characteristics, however, are likely to reveal possible discrepancies in smart city attitudes at a more fundamental level. Our study, therefore, focuses on these attributes to reveal whether existing social inequalities are already reflected in attitudes towards smart city technologies. This aspect has been largely ignored in previous research.

3 Data and operationalization

The data analyzed in this paper were collected in May 2023 through Forsa Omninet, a probability-based online panel in Germany. Forsa Omninet currently consists of 100,000 German-speaking panelists aged 14 and older. The panelists are recruited offline through Forsa's regular multi-topic telephone survey, Forsa Omnitel. For this study, respondents were randomly selected from the panel to approximate the distribution of gender, age, and region in the German population.

The survey questions covered a range of topics: in addition to the smart city questions and sociodemographic characteristics analyzed here, we collected information on respondents' everyday mobility, evaluation of public transport at their place of residence, environmental and fairness attitudes, and technological affinity and knowledge. In total, 2021 respondents completed the survey.

3.1 Smart city attitudes

The questions regarding smart city applications were prefaced by an introductory sentence describing them as "various technologies that either could be used or are already in use in cities and towns." We deliberately refrained from using the term *smart city* or a specific definition to avoid priming respondents. Since the applications that fall under this term may also be unfamiliar, we embedded them in short descriptive sentences. The selected applications are based on real-world examples of smart city technologies (Zubizarreta et al. 2016) that cover four broad domains (mobility, social inclusion, public safety, and environment). An overview of the eleven applications and the introductory sentences is shown in Table 1. See Online Resource 1 in the Supplementary Information for the German wording of the descriptive sentences.

Regarding smart city applications, we measured whether respondents were familiar with them and how desirable they were. Each respondent was shown five randomly chosen applications and was asked about the familiarity and desirability items for the selected applications. For the exact wording of the questions in German and their English translations, see Online Resource 2.

3.1.1 Familiarity

To measure respondents' familiarity with the smart city applications, they were asked whether they had heard or read about them. They could answer either "Yes" or "No."

3.1.2 Desirability

Next, to measure the desirability of the applications, we asked the respondents how much they would like or dislike

Table 1 Smart city applications, along with short explanatory sentences, as presented to survey respondents

Application type/domain	English translation	Application label used in this paper
Mobility	Public bicycles that can be rented via an app	Smart bikes
	Smart cars that share data with road sensors and other vehicles to improve traffic flow	Smart cars
	Smart buses that dynamically adapt their route to the needs of passengers	Smart buses
	Sensors at parking lots that show available parking spaces	Parking sensors
Social inclusion	Sensors throughout the city that are connected to apps used by visually impaired individuals to help them better navigate the city	Navigation sensors
	Sensors that measure pedestrian and wheelchair traffic to improve urban planning	Mobility sensors
Public safety	Street cameras that automatically monitor whether traffic rules are being followed	Traffic cameras
	Security cameras in public spaces to prevent crime	Security cameras
	Sensors that adapt urban lighting to the current behavior of the inhabitants	Lighting sensors
Environment	Smart grid that adapts the flow of electricity to current demand	Smart grid
	Sensors that measure air quality and noise to derive measures to improve both livability and climate protection	Pollution sensors

the applications' implementation in their residential area. Respondents could answer on a six-point scale ranging from "I would not like it at all" to "I would like it very much." For the latent class analysis, we combined the two outer categories at the positive ("I would like it" and "I would like it very much") and negative ("I would not like it" and "I would not like it at all") extremes of the scale into single categories ("I would like it [very much]" and "I would not like it [at all]").

3.2 Sociodemographic characteristics

Apart from the smart city items, we collected information on respondents' sociodemographic characteristics.

3.2.1 Gender

Respondents' gender was measured using a semi-openended question in which respondents indicated whether they were female, male, or identified with another gender (with the option of providing an open answer). Three respondents stated they were neither female nor male, but did not use the open text field for specification. The low number of these cases does not allow us to include them in our statistical analysis in a meaningful way. Thus, we coded these three cases as missing values. Regarding the gender distribution across the sample, 50.2% of respondents identified as female.

3.2.2 Age

Respondents' age was measured in years. For further analyses, we recoded the age variable into a categorical variable with three levels (18–39 years, 40–59 years, and 60 years and older). Regarding age, 33.7% of the respondents are between 18 and 39, 34.3% between 40 and 59, and 32% are 60 and older.

3.2.3 Education

Respondents' education was measured using questions about respondents' general and vocational education. For our analyses, we created a categorical variable from the survey measurements that indicates whether they have a low, medium, or high education level according to the International Standard Classification of Education (ISCED). Most respondents, i.e., 50.8%, reported having a medium education level, followed by 45.8% with a high education level. The remaining 3.4% of respondents have a low level of education.

3.2.4 Migration background

A binary variable was used to measure respondents' migration background. Migration background was defined as whether the respondent or one of their parents was born outside Germany. 11.5% of the respondents reported having a migration background.

3.2.5 Mobility impairment

A binary variable was used to measure whether respondents have a mobility impairment. 11.3% of the respondents indicated having a mobility impairment.

3.2.6 Household income

Respondents' household income was measured as the net household income of all household members: ≤520€, 521€–<750€, 750–<1500€, 1500€–<2500€, 2500€–<3500€, 3500€–<5000€, and ≥5000€. For the analysis, the levels ≤520€, 521€–<750€, and 750–<1500€ were combined into one category. In terms of distribution, 8.5% of the respondents reported a household income below 1500 €, 18.9% between 1500 € and less than 2500 €, 21.6% between 2500 € and less than 3500 €, 27% between 3500 € and less than 5000 €, and 24.1% reported a household income of 5000 € or more.

3.2.7 Urbanicity

The urbanicity of respondents' residential neighborhood was measured with a four-level categorical variable that indicates whether respondents live in a rural area, in a medium-sized or small town (<100,000 inhabitants), in a metropolitan suburb, or in a metropolitan area (≥100,000 inhabitants). 25.1% of respondents reported living in a rural area, 37.4% in a small or medium-sized town. 9.7% of respondents live in a metropolitan suburb, and the remaining 27.8% in a metropolitan area.

The univariate statistics for all variables are presented in Online Resource 3.

4 Analytical approach

To gain a general picture of respondents' familiarity with smart city applications, we compare the ratio of "Yes" and "No" responses. Regarding desirability, we calculate each application's mean value. For this purpose, we treat the desirability variables as quasi-metric and use all six answer categories for each variable, respectively.

Next, we use latent class analysis (LCA) to answer our research question, i.e., examine the patterns underlying public attitudes toward smart city applications and the individual characteristics that shape these patterns. This method allows us to identify latent classes based on the observed data. Since we are interested in the distinct patterns underlying respondents' familiarity with and desirability of the smart city applications, we conduct two LCAs, one for the familiarity and one for the desirability items.

Applying LCA, we follow the bias-adjusted three-step approach (Vermunt 2010): first, we build the latent class model without covariates to identify the number of latent classes based on a set of variables (step 1). Then we assign the respondents to the identified classes based on their response patterns regarding those variables (step 2). Finally, we examine whether external variables are associated with respondents' class membership (step 3).

We used R (Version 4.3.1, R Core Team 2025) for data cleaning and visualisations, and LatentGOLD (Version 6.1, Vermunt and Magidson 2025) for the bias-adjusted three-step LCA.

4.1 Missing values

The dataset contains many missing values since each respondent was asked about only five of the eleven smart city applications. These missing values can be included in the LCA using LatentGOLD, assuming they are missing at random (MAR). This assumption is likely to hold because the five applications were randomly assigned to respondents. We therefore include the missing values in the LCA.

4.2 Technical settings while conducting LCA

We made the following changes in LatentGOLD when identifying the optimal number of classes (step 1 of the LCA): i. we extended the output section to include bootstrap *p*-values, ii. we included the missing values in the variables used to identify the optimal number of classes, iii. we increased the start values, i.e., the number of random sets to 160 and the number of iterations per start set to 250. We also applied the latter setting (random sets and iterations) when modeling the relationship between class membership and covariates (step 3 of the LCA).

5 Results

5.1 Univariate results

Figure 1 presents the distribution of respondents' familiarity and unfamiliarity with the applications. Overall, the degree of familiarity varies considerably between the individual applications. Safety cameras are the most familiar smart city application, followed by smart bikes and pollution sensors. In contrast, respondents are least familiar with applications aimed at improving inclusivity, i.e., navigation and mobility sensors.

Next, Fig. 2 depicts the average desirability of each of the eleven smart city applications. Most applications are

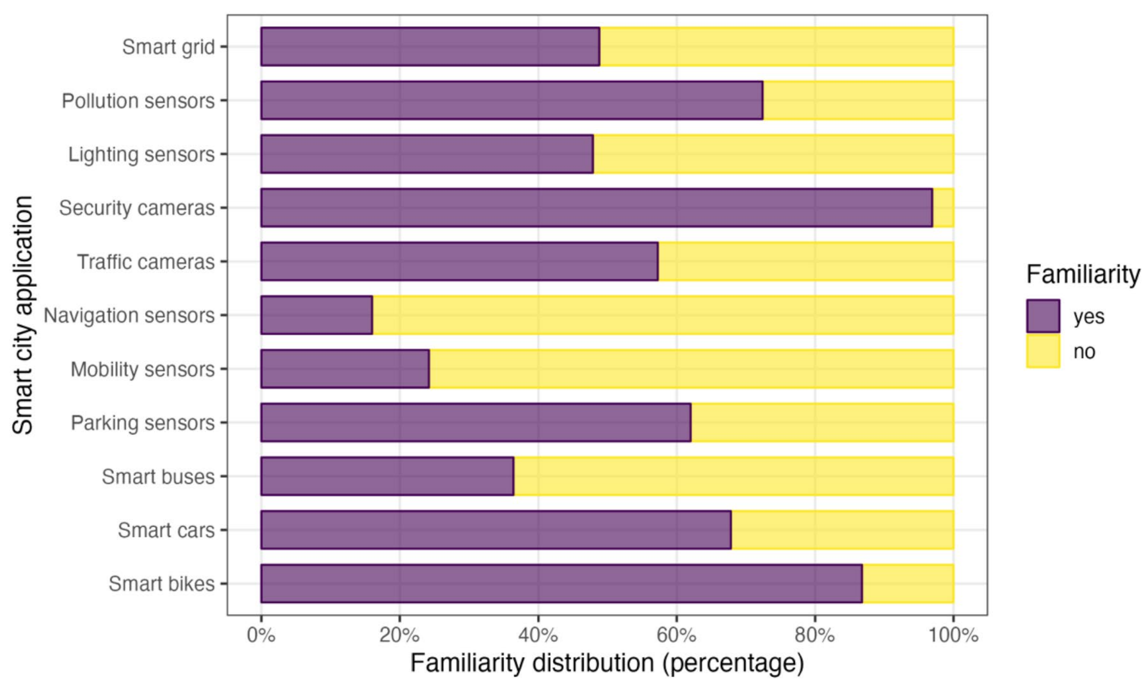

Fig. 1 Distribution of (un)familiarity with smart city applications. Note: Each respondent answered the familiarity question based on five randomly chosen applications, which were the same for the desirability question.

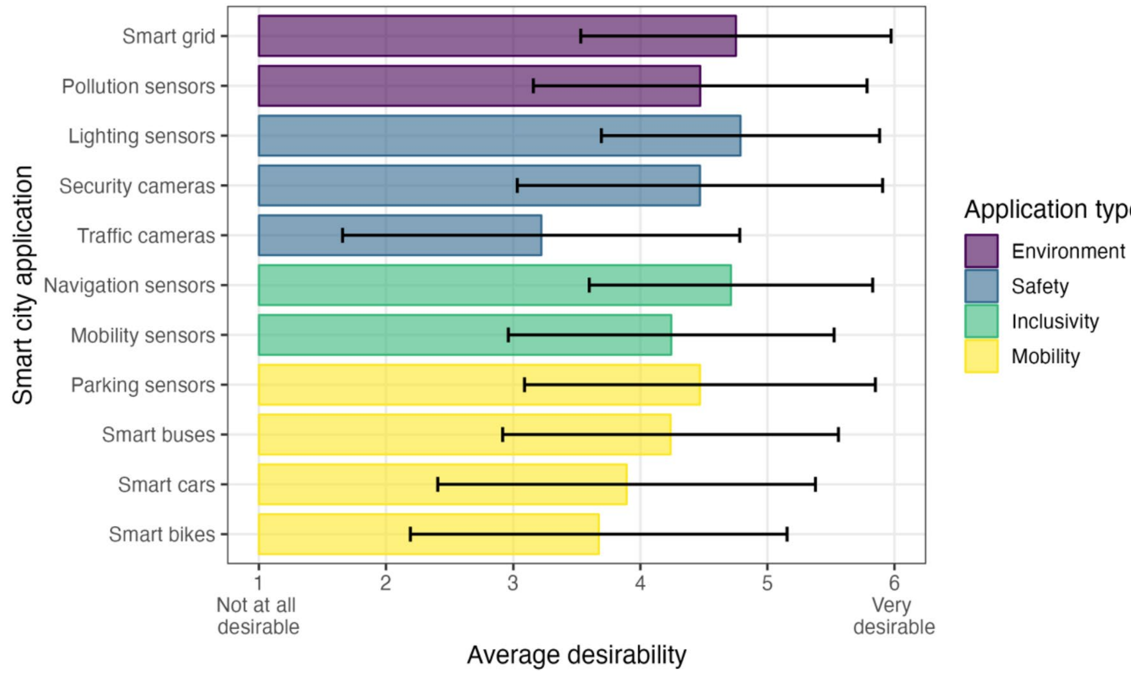

Fig. 2 Average desirability of smart city applications. Note: Each respondent answered the desirability question based on five randomly chosen applications, which remained the same for the familiarity question; whiskers represent the standard deviation.

desirable, with modest differences in average desirability between individual applications. One exception to this pattern is traffic cameras, which are the least desirable. The most desirable applications are smart grid, lighting, and navigation sensors.

5.2 LCA results

To determine the optimal number of latent classes (step 1), we estimated a series of latent class (LC) models with the familiarity and desirability variables separately, increasing the number of classes from one to ten. Typically, the model with the lowest Bayesian Information Criterion (BIC) is considered the most appropriate (Magidson and Vermunt 2004). For familiarity, the two-class model had the lowest BIC; for desirability, it was the three-class model. Online Resources 4 and 5 summarize the fit criteria for all models.

LCA relies on the assumption of local independence, meaning that after accounting for latent class membership, the observed variables are assumed to be uncorrelated within each class (Magidson and Vermunt 2004). Whether this assumption is violated is indicated by the magnitude of the bivariate residuals (BVRs). BVR values are based on Pearson's chi-squared test statistics, adjusted by the degrees of freedom, and assess how much the observed frequencies of the variable pairs deviate from the expected counts estimated under the respective LC model (Magidson and Vermunt 2004). BVRs substantially larger than one may indicate local dependencies. The two-class familiarity model and the three-class desirability model initially showed high BVRs for some variable pairs (see Online Resources 6 and 7 for all BVRs from the initial familiarity and desirability LC models).

One solution to relax the assumption of local independence is to fit the respective model again and extend it by including "direct effects," i.e., by allowing certain observed variables to remain correlated even after conditioning on class membership (see Magidson and Vermunt (2004) for a detailed description of this procedure). Accordingly, we re-estimated the respective models, now including the direct effect parameters of those variable pairs for which the BVRs were greater than one and had associated p-values below 0.01 (those BVRs are marked bold in Online Resources 6 and 7). The BVRs of the re-estimated models decreased to an acceptable level (see maximum BVRs in Models F11 and D11 in Online Resources 4 and 5, respectively). We used these models for the further steps of the LCA.

After determining the optimal number of latent classes for each set of variables, we extracted each respondent's posterior class membership probabilities, i.e., the probability of belonging to each latent class based on their response pattern. We used modal assignment, i.e., each respondent was assigned the class for which their posterior probability was highest.

In the final step of the LCA, we examined the association between the identified classes and sociodemographic variables using pairwise Wald tests. The variables included gender, age, education, mobility impairment, migration background, urbanicity, and household income.

In the following subsections, we describe the subsequent LCA procedure separately for the familiarity with and desirability of smart city applications.

5.2.1 LCA: Familiarity

Based on the familiarity variables, we identified two distinct classes that we labeled "Self-declared novices" and "Self-declared insiders" (see Table 2 for the conditional response probabilities). The classes comprise 51.84% and 48.16% of respondents, respectively.

The "Self-declared novices" show generally low familiarity with most smart city applications. Familiarity is particularly low for technologies that improve social inclusion, i.e., mobility and navigation sensors, where the probability of a negative response exceeds 95%. For pollution sensors, parking sensors, and smart cars, familiarity and unfamiliarity are more evenly balanced, though the probability of a negative response is still higher. An exception to this pattern is smart bikes and security cameras, which are familiar even among the "Self-declared novices" with probabilities for a positive response at 78% and 94%, respectively.

In contrast, the "Self-declared insiders" show high familiarity across most smart city applications, ranging from 60% for smart buses to 100% for security cameras. The only exceptions are, similarly to the class described previously, mobility and navigation sensors for which the probabilities of a negative response are 55% and 68%, respectively.

Next, we examined the differences between the two classes regarding sociodemographic characteristics. Table 3 shows the class-specific probabilities of the covariates together with the Wald test statistics and significant pairwise comparisons. We find significant differences in the distribution of gender, education, and household income. While male respondents are more likely to be in the "Self-declared insiders" class at 69%, female respondents are significantly more represented among the "Self-declared novices" at 66%.

Individuals who reported having a medium education level are more likely to be among the "Self-declared novices" at 57% compared to the 44% in the other class. Those who reported having a high education level have a higher probability of being among the "Self-declared insiders" at 53% compared to the 40% in the "Self-declared novices" class.

Respondents who reported having a household income of 1500€ or above, but below 3500€, have a higher probability of being among the "Self-declared novices" (22% and 25%, respectively) compared to the other class (15% and 18%, respectively). Respondents who reported having a household income of at least 3500€ are, conversely, more likely to be in the "Self-declared insiders" class (30% and 28%, respectively) in comparison to the "Self-declared novices" (25% and 21%, respectively).

Table 2 Conditional response probabilities for the familiarity with each smart city application by latent class

Variables	Class 1 *Self-declared novices*	Class 2 *Self-declared insiders*	Overall
Class size	51.84%	48.16%	
Smart bikes			
No	0.22	0.04	0.13
Yes	0.78	0.96	0.87
Smart cars			
No	0.54	0.08	0.32
Yes	0.46	0.92	0.68
Smart buses			
No	0.85	0.40	0.63
Yes	0.15	0.60	0.37
Parking sensors			
No	0.56	0.17	0.37
Yes	0.44	0.83	0.63
Mobility sensors			
No	0.96	0.55	0.76
Yes	0.04	0.45	0.24
Navigation sensors			
No	0.98	0.68	0.84
Yes	0.02	0.32	0.16
Traffic cameras			
No	0.67	0.17	0.43
Yes	0.33	0.83	0.57
Security cameras			
No	0.06	0.00	0.03
Yes	0.94	1.0	0.97
Lighting sensors			
No	0.75	0.26	0.51
Yes	0.25	0.74	0.49
Pollution sensors			
No	0.51	0.05	0.29
Yes	0.49	0.95	0.72
Smart grid			
No	0.80	0.22	0.52
Yes	0.20	0.78	0.48

5.2.2 LCA: Desirability

Based on the desirability variables, we identified three distinct classes that we labeled "Cautious supporters," "Strong supporters," and "Reluctant skeptics" (see Table 4 for the conditional response probabilities). The classes represent 64.99%, 27.45%, and 7.56% of respondents.

Table 3 Differences in probabilities between the two familiarity classes regarding sociodemographic characteristics

Variable	Overall	Class 1 *Self-declared novices*	Class 2 *Self-declared insiders*	Wald statistic	Significant pairwise class comparisons*
Class size		51.37%	48.63%		
Gender				96.29*	1 versus 2
Male	0.51	0.34	0.69		
Female	0.49	0.66	0.31		
Age				5.62	–
18–39 years	0.35	0.34	0.36		
40–59 years	0.34	0.36	0.33		
60 years and more	0.31	0.30	0.32		
Mobility impairment				3.85	–
No	0.89	0.90	0.87		
Yes	0.11	0.10	0.13		
Education level				11.38*	1 versus 2
Low	0.03	0.03	0.03		
Medium	0.51	0.57	0.44		
High	0.46	0.40	0.53		
Migration background				1.61	–
No	0.88	0.88	0.89		
Yes	0.12	0.12	0.11		
Urbanicity				3.79	–
Rural area	0.25	0.27	0.23		
Small or medium-sized town	0.37	0.35	0.39		
Metropolitan suburb	0.09	0.08	0.10		
Metropolitan area	0.29	0.30	0.28		
Household income				17.60*	1 versus 2
<1500€	0.08	0.08	0.08		
1500€–<2500€	0.19	0.22	0.15		
2500€–<3500€	0.22	0.25	0.18		
3500€–<5000€	0.27	0.25	0.30		
≥5000€	0.24	0.21	0.28		

*Significant at the 0.01 level

The "Cautious supporters" class is characterized by a generally positive attitude toward smart city technologies, though with some variation across specific applications. This group is neither highly enthusiastic about the technologies nor strongly opposed. The highest probabilities of positive responses, ranging between 77% and 89%, are observed for smart grids (26% for "I would rather like it" and 63% for "I would like it [very much]"), pollution sensors (31% and 49%, respectively), lighting sensors (27% and 60%), navigation sensors (33% and 54%), and parking sensors (26% and 51%).

This group also mostly welcomes smart buses, mobility sensors, and security cameras, with 69% to 75% of the probability falling into the two positive response categories. However, a notable share of responses for these applications falls into the moderately negative category ("I would rather not like it"), with 22% for both smart buses and mobility sensors, and 14% for security cameras.

The remaining three applications, smart bikes, smart cars, and traffic cameras, show a more mixed pattern. For smart cars and smart bikes, 53% of the probability is in the moderately or strongly positive categories. In contrast, traffic cameras are viewed more critically: 63% of the probability falls into the two negative response categories, making it the least favored application among the "Cautious supporters."

The second class, "Strong supporters," expresses a much more enthusiastic attitude toward smart city applications. For most technologies, the probability of rating them as (very) desirable is particularly high, reaching 90% or more for applications such as smart grid, pollution sensors, lighting sensors, and navigation sensors. As with the previously described class, traffic cameras remain an exception: it is

Table 4 Conditional response probabilities for the desirability of each smart city application by latent class

Variables	Class 1 *Cautious supporters*	Class 2 *Strong supporters*	Class 3 *Reluctant skeptics*	Overall
Class size	64.99%	27.45%	7.56%	
Smart bikes				
I would not like it [at all]	0.21	0.06	0.96	0.22
I would rather not like it	0.27	0.14	0.04	0.21
I would rather like it	0.25	0.25	0.00	0.23
I would like it [very much]	0.28	0.55	0.00	0.33
Mean	**2.59**	**3.29**	**1.04**	**2.67**
Smart cars				
I would not like it [at all]	0.19	0.01	0.65	0.17
I would rather not like it	0.28	0.05	0.26	0.21
I would rather like it	0.25	0.18	0.07	0.22
I would like it [very much]	0.28	0.75	0.02	0.39
Mean	**2.63**	**3.69**	**1.47**	**2.83**
Smart buses				
I would not like it [at all]	0.10	0.00	0.56	0.11
I would rather not like it	0.22	0.01	0.30	0.17
I would rather like it	0.34	0.14	0.11	0.26
I would like it [very much]	0.35	0.85	0.03	0.46
Mean	**2.93**	**3.83**	**1.61**	**3.08**
Parking sensors				
I would not like it [at all]	0.12	0.01	0.40	0.11
I would rather not like it	0.11	0.02	0.19	0.09
I would rather like it	0.26	0.15	0.22	0.23
I would like it [very much]	0.51	0.82	0.19	0.57
Mean	**3.16**	**3.79**	**2.19**	**3.26**
Mobility sensors				
I would not like it [at all]	0.08	0.00	0.66	0.10
I would rather not like it	0.22	0.01	0.26	0.16
I would rather like it	0.37	0.13	0.06	0.28
I would like it [very much]	0.34	0.86	0.01	0.46
Mean	**2.97**	**3.85**	**1.42**	**3.10**
Navigation sensors				
I would not like it [at all]	0.04	0.00	0.25	0.04
I would rather not like it	0.09	0.00	0.22	0.07
I would rather like it	0.33	0.09	0.33	0.27
I would like it [very much]	0.54	0.90	0.20	0.62
Mean	**3.38**	**3.90**	**2.47**	**3.45**
Traffic cameras				
I would not like it [at all]	0.35	0.17	0.77	0.33
I would rather not like it	0.28	0.22	0.19	0.26
I would rather like it	0.17	0.21	0.03	0.17
I would like it [very much]	0.20	0.39	0.01	0.24
Mean	**2.21**	**2.83**	**1.28**	**2.31**
Security cameras				
I would not like it [at all]	0.11	0.07	0.20	0.11
I would rather not like it	0.14	0.10	0.20	0.13
I would rather like it	0.22	0.21	0.24	0.22
I would like it [very much]	0.53	0.63	0.36	0.55
Mean	**3.18**	**3.39**	**2.76**	**3.20**

Table 4 (continued)

Variables	Class 1 *Cautious supporters*	Class 2 *Strong supporters*	Class 3 *Reluctant skeptics*	Overall
Lighting sensors				
I would not like it [at all]	0.03	0.00	0.25	0.04
I would rather not like it	0.10	0.00	0.29	0.09
I would rather like it	0.27	0.06	0.27	0.21
I would like it [very much]	0.60	0.94	0.20	0.66
Mean	**3.44**	**3.94**	**2.41**	**3.50**
Pollution sensors				
I would not like it [at all]	0.06	0.00	0.56	0.08
I would rather not like it	0.14	0.01	0.28	0.12
I would rather like it	0.31	0.09	0.12	0.23
I would like it [very much]	0.49	0.90	0.04	0.57
Mean	**3.23**	**3.89**	**1.65**	**3.29**
Smart grid				
I would not like it [at all]	0.04	0.00	0.40	0.06
I would rather not like it	0.07	0.01	0.20	0.06
I would rather like it	0.26	0.09	0.23	0.21
I would like it [very much]	0.63	0.90	0.17	0.67
Mean	**3.48**	**3.90**	**2.16**	**3.49**

the only application with probabilities distributed across all response categories, making it the least favored technology among the “Strong supporters.”

The third class, “Reluctant skeptics,” is marked by generally reserved or ambivalent attitudes toward smart city applications. For pollution sensors, traffic cameras, mobility sensors, smart buses, and smart cars, the probability of falling into one of the two negative response categories ranges from 84% to 96%. Smart bikes are the least favored technology in this group, with a 96% probability of receiving the most negative response. However, the picture is more differentiated for the remaining applications, with probabilities distributed across all response categories. Notably, for security cameras and navigation sensors, the probability of a positive response is higher than that of a negative one.

Turning to the class-specific probabilities of the covariates, we find significant differences in the distribution of gender and urbanicity (Table 5). Male respondents have a higher probability of being in either the “Strong supporters” (62%) or “Reluctant skeptics” (72%) classes compared to the “Cautious supporters” (45%). Conversely, women are significantly more frequently represented in the “Cautious supporters” group at 55% compared to the “Strong supporters” and “Reluctant skeptics,” where they account for 38% and 28%, respectively. Individuals living in rural areas are more likely to be in the “Reluctant skeptics” class (54%) compared to the other classes (24% among the "Cautious supporters" and 19% among the "Strong supporters"). In contrast, inhabitants of urban areas (both small/medium towns and metropolitan areas as well as their suburbs) are more likely to be in the first two classes, i.e., "Cautious supporters" and "Strong supporters," compared to the “Reluctant skeptics.”

6 Discussion

This study investigated the patterns underlying public attitudes toward smart city applications and how individuals’ characteristics shape these patterns. Applying an exploratory approach, we used the bias-adjusted three-step LCA (Vermunt 2010) to find latent classes based on the familiarity with and desirability of eleven smart city applications. Our analysis revealed two distinct familiarity classes: "Self-declared novices” and “Self-declared insiders.” Similarly, we identified three desirability classes: “Cautious supporters,” “Strong supporters,” and “Reluctant skeptics."

The examination of the relationship between class membership and sociodemographic characteristics showed significant differences in class-specific probabilities in terms of gender (for familiarity and desirability classes), education (familiarity classes), household income (familiarity classes), and urbanicity (desirability classes).

Regarding familiarity with smart city technologies, men, respondents who reported having a high education level, and those having a household income of at least 3500€ are more likely to be among the “Self-declared insiders.” In contrast, their counterparts, i.e., women, respondents with a medium education level, and those who reported a household income below 3500€, are more likely to be among the “Self-declared novices.”

Table 5 Differences in probabilities between the three desirability classes regarding sociodemographic characteristics

Variables	Overall	Class 1 *Cautious supporters*	Class 2 *Strong supporters*	Class 3 *Reluctant skeptics*	Wald statistic	Significant pairwise class comparisons*
Class size		65.22%	27.96%	6.83%		
Gender					20.67*	1 versus 2; 1 versus 3
Male	0.51	0.45	0.62	0.72		
Female	0.49	0.55	0.38	0.28		
Age					2.98	–
18–39 years	0.35	0.36	0.35	0.26		
40–59 years	0.34	0.33	0.35	0.42		
60 years and more	0.31	0.31	0.31	0.32		
Mobility impairment					0.09	–
No	0.89	0.89	0.89	0.88		
Yes	0.11	0.11	0.11	0.12		
Education level					8.88	–
Low	0.03	0.02	0.03	0.08		
Medium	0.51	0.52	0.50	0.43		
High	0.46	0.46	0.47	0.50		
Migration background					5.01	–
No	0.88	0.90	0.83	0.90		
Yes	0.12	0.10	0.17	0.10		
Urbanicity					31.71*	1 versus 3; 2 versus 3
Rural area	0.25	0.24	0.19	0.54		
Small or medium-sized town	0.37	0.39	0.36	0.27		
Metropolitan suburb	0.09	0.10	0.09	0.01		
Metropolitan area	0.29	0.27	0.36	0.18		
Household income					6.43	–
<1500€	0.08	0.09	0.07	0.07		
1500€–<2500€	0.19	0.19	0.18	0.13		
2500€–<3500€	0.22	0.22	0.18	0.28		
3500€–<5000€	0.27	0.27	0.28	0.25		
≥5000€	0.24	0.22	0.29	0.28		

*Significant at the 0.01 level

In terms of desirability, inhabitants of rural areas show the strongest aversion towards smart city applications, being more likely among the "Reluctant skeptics"; inhabitants of urban areas, on the other hand, are more likely to be among the "Strong supporters" of such technologies. Further, men are more likely to be either among the "Strong supporters" or "Reluctant skeptics." In contrast, their female counterparts are more likely to have a nuanced attitude and be among the "Cautious supporters."

6.1 Disparities in attitudes toward smart city applications as a reflection of multidimensional (urban) inequality?

Our analysis of the association between the identified latent classes and covariates revealed significant differences that align with familiar patterns. As discussed in Section 2.1, the vision of the smart city is shaped by the prevailing socio-political context (Kitchin et al. 2019; Vanolo 2014). Consequently, the smart city not only reflects but also likely reproduces the unequal social relations already present in urban environments. Urban space, regardless of digital technologies, has always been an arena of asymmetrical power relations along dimensions such as gender (Gough 2016), age (Valentine 2025), or socioeconomic status (van Ham et al. 2021). Modern urban planning continues to prioritize the needs of a relatively narrow group defined by specific (often intersecting) characteristics: men and able-bodied, affluent individuals of working age. Other groups, such as children and adolescents, older adults, low-income residents or those with disabilities, and women, are frequently marginalized within urban spaces and must adapt to conditions that do not meet their needs regarding fundamental aspects of (urban) life such as safety (Cui et al. 2023), daily routines (Bhattacharya 2025), recreation (Phillips et al. 2022), or mobility (Xu et al. 2025).

Urban inequality manifests in many forms and affects a wide range of social groups. Much of the existing research has concentrated on gendered dimensions of urban space, given that women experience disproportionately high levels of violence and harassment in public areas (Fairchild 2023; Gough 2016). Although women and men inhabit the same environments, their experiences of these spaces differ markedly due to these heightened risks, which in turn shape how women move through and engage with the city. The advent of the smart city does not automatically lead to a change in these conditions. Although smart city initiatives are framed as making urban spaces more sustainable and livable, they remain oriented toward the interests of groups that already occupy privileged positions. As mentioned in previous sections, it is primarily corporations, and within them, predominantly men, who shape smart city planning (Maalsen et al. 2023). Efforts to involve citizens often fall short, as planning processes are typically top–down and offer residents little real influence over the implementation of technologies (Spicer et al. 2023). As a result, many applications prioritize corporate objectives such as efficiency or sustainability, while the needs of structurally disadvantaged groups remain overlooked.

While our findings are exploratory, they underline that citizens cannot be understood as a homogeneous group in terms of the definition of a "smart citizen" (Kitchin et al. 2019). The identified sociodemographic differences in attitudes toward smart city applications likely reflect more profound disparities in fundamental needs and preferences regarding urban space. Notably, we found significant gender differences regarding both familiarity and desirability. This suggests that the applications we introduced in the survey may be less appealing to women, as they neither incorporate their perspectives nor align with their lived realities (see Section 7 for further discussion). Among the wide range of corporate-led smart city applications, only a few initiatives explicitly account for these differences and attempt to address the needs of specific subgroups. For instance, German and colleagues (2023) review a variety of technologies aimed at improving women's safety and accessibility in urban environments. However, as the authors conclude, these applications enhance women's feelings of safety only to a limited extent, as they fail to address the full range of factors that contribute to women's insecurity and fear in public spaces. This has important implications for the truly inclusive design of smart cities, which we discuss further in Section 6.3.

6.2 The ambivalence of desirability and a critical reflection on smart cities

Another finding of our study is that, overall, respondents find the smart city applications desirable (see Section 5.1). This can be interpreted in a narrow sense, i.e., in the context of each specific application. However, the general desirability of the presented smart city applications might reflect a broader sentiment, i.e., a more profound desire for improvements to current conditions, or in other words, a *better future*. It is therefore unsurprising that individuals perceive the technologies as desirable when presented with them as tools for achieving these goals. From this perspective, citizens' wishes align with the optimistic promises made by stakeholders that drive the smart city agenda. The more pertinent question, however, is whether different stakeholder groups, such as citizens, urban administrations, and private companies, share a common vision for *how* these desires should be realized. As shown by Spicer et al.'s (2023) findings (see Section 2.2), this vision is likely to differ between the mentioned stakeholder groups, which is reflected in the misalignment of priorities regarding which urban problems are being addressed in the smart city context.

In this regard, the terminology we used in our survey needs to be addressed. Although we did not explicitly mention the term *smart city*, we described some applications as *smart* (see Table 1). Such framing may have contributed to the generally positive attitude towards the applications (see Section 7 for further discussion). After all, who would find *smartness* undesirable? Or, to revisit Lindner and Meissner's (2018:10) question from the introduction to this paper: "who wants to live in a dumb city"? Apparently, no one. The fact that smart city agendas strategically exploit the positive connotations of *smartness*, despite the term's fuzziness and vagueness, has been discussed in academic critique (Cugurullo 2018). Considering that many regions worldwide now aspire to become smart cities, it is worth critically reflecting on what *smart* actually means. Technological solutions are not automatically the *best*. The goals that smart cities seemingly pursue (e.g., environmental goals) do not necessarily require an application, but rather bold and progressive policies that prioritize the collective well-being of all civic groups, the significance of which extends beyond the respective legislative period. For example, achieving environmental goals will remain difficult if urban mobility and infrastructure remain geared toward cars, which dominate many cityscapes and contribute heavily to environmental and noise pollution (Nieuwenhuijsen 2024). Measuring pollution with sensors or optimizing traffic flow through smart traffic management systems may reduce congestion. Still, it will not reduce the number of cars or encourage individuals to adopt more sustainable mobility habits.

6.3 Implications for smart city practitioners and researchers

Based on the points discussed previously, we identify implications for key stakeholders involved in the smart city transformation and social scientists studying them.

Urban development toward smart cities does not occur in a vacuum. It involves the collection of citizen data, the automation of urban processes, and the integration of technologies into everyday living spaces. Smart cities must therefore be understood in the context of existing (urban) inequality along dimensions such as gender, age, or income. Smart city practitioners must recognize that different social groups experience urban spaces in distinct ways and bring diverse needs and expectations to the idea of a smart city. This also requires acknowledging that urban environments are still shaped by norms and priorities that largely reflect male interests. A meaningful transformation of urban spaces therefore demands active engagement with these biases to ensure that smart city technologies do not simply reproduce existing inequalities.

Another implication for practitioners is that an equitable transformation of urban spaces is only possible if citizens' needs are genuinely considered and they are meaningfully included in decision-making. Previous attempts at citizen participation have often fallen short because they were largely top–down, treating citizens as a passive and homogeneous stakeholder group (Spicer et al. 2023). As the review of technologies aimed at enhancing women's safety illustrates, even well-intentioned initiatives frequently fail to fully incorporate the perspectives of the groups they are meant to serve (German et al. 2023). Taken together, this suggests that citizens have played a marginal role in the smart city discourse so far, despite being the ones who ultimately live with these technologies in their immediate environments. Municipal administrations and smart city practitioners should therefore place citizens' interests at the center of smart city development, ensuring that ongoing urban transformations become an opportunity to empower residents and foster sustained civic engagement.

Another critical point for smart city practitioners concerns the effectiveness and scope of smart city technologies. The dominant narrative often presents these applications as *the solution* to urban challenges. Yet critical research shows that the smart city discourse tends to focus narrowly on environmental issues (Vanolo 2014), while overlooking other pressing problems such as rising housing costs or the decline of public spaces. However, even in the environmental domain, smart city technology alone is not the solution. Utrecht, for instance, pursues a strategy to make the city more inclusive and improve citizens' quality of life[1] without digressing into the smart city narrative. The city invests in new parks and infrastructure, prioritizing cycling and public transportation. Utrecht is taking a holistic approach towards sustainability rather than focusing on isolated solutions in single areas. Cities like that can serve as role models for urban areas in other regions to follow.

Ultimately, our study has implications for social scientists researching smart cities using a quantitative approach. In previous studies, respondent characteristics such as gender, education, income, age, or neighborhood have played only a minor role, being excluded from the analysis or treated as control variables. Quantitative research on smart cities would greatly benefit from giving these characteristics greater weight both as analytical categories and interpretative lenses. Doing so enables examining differences in attitudes along key axes of inequality. Identifying those disparities is the first step towards overcoming them.

7 Strengths and limitations

The major strength of our study is the combination of a high-quality survey sample and a quantitative analytical approach. Specifically, using a probability-based sample allows for the generalization of our results onto a larger population (the German adult residential population, in our case). Further, the quantitative methods applied in this paper reveal trends within the general public regarding the desirability of and familiarity with smart city applications. Both aspects make this study essential to the primarily qualitative research field on attitudes towards smart cities.

However, this study also has its limitations. First, although we refrained from explicitly using the term "smart city" or its definition in the survey to avoid priming the respondents, we embedded the applications in short descriptive sentences (see Table 1) to avoid ambiguity. However, our wording may have influenced respondents' evaluations. For example, we introduced security cameras as a measure to *prevent crime*, which may have contributed to the high average desirability of the smart city technologies. That is, in a different context, the purpose of the same technology may be interpreted quite differently, for instance, as a tool for automated surveillance, making this application ethically questionable. Consequently, a more neutral description could have resulted in respondents taking a more critical stance. An experimental approach to compare how different framings of smart city applications (e.g., optimistic vs.

[1] https://healthyurbanliving.utrecht.nl/our-vision-for-utrecht-in-2040 (accessed September 30, 2025)

critical vs. neutral) affect public attitudes represents a compelling avenue for future research.

Second, although our survey included a variety of smart city technologies, the applications presented to respondents were predominantly corporate, top–down solutions primarily shaped by a male experience of the city. Missing from our selection were initiatives that foster social cohesion, e.g., by facilitating intergenerational encounters between citizens (Yarker 2021). Given the gender differences identified in attitudes toward smart cities, our selection also lacks applications developed from a feminist perspective, e.g., those explicitly designed to increase women's safety in urban spaces (Osipova and Hornecker 2023). Future research should expand the scope beyond corporate-led applications to include bottom–up initiatives rooted in community engagement. Moreover, future studies could examine how citizens subjectively perceive and envision a "smart city" without relying on predefined examples of applications.

Third, we operationalized familiarity and desirability using general questions that limit our ability to explore the nuances behind the constructs. Specifically, the binary familiarity measure may not have fully captured differences between superficial awareness and a more substantive understanding of the technologies. Likewise, the desirability question does not distinguish between general approval and an actual wish to see such technologies implemented in respondents' residential areas. Future research should expand our measurements to gain a more nuanced insight into smart city attitudes.

Fourth, although the analyzed data come from a probability-based panel, the generalizability of the findings is subject to certain limitations. Not every city pursues a uniform smart city strategy, which depends on factors such as infrastructure, local demand, and financial resources. These factors influence the actual deployment of technologies and how desirable residents perceive them. In addition, as with any survey-based research, the possibility of nonresponse bias must be acknowledged. While efforts were made to ensure a balanced and representative sample, differential participation may still influence the results, especially if certain attitudes or demographic groups are underrepresented.

Fifth, this study is exploratory, and the data analyzed are cross-sectional. Therefore, we cannot draw any conclusions about causal relationships. We also did not ask respondents to elaborate on the motivations behind their desirability ratings, which limits the depth of our data regarding the values and experiences that shaped these attitudes. Future survey-based research should incorporate open-ended questions to complement quantitative data, as such responses can reveal interpretive nuances and contextual factors that closed items cannot capture. The research field would also benefit from mixed-methods and qualitative designs, such as studies that adopt a participatory approach involving community members or focus groups, for specific smart city applications. They could provide deeper insights into the cultural, ethical, and emotional dimensions of civic engagement with smart city technologies, which remain difficult to access through standardized survey instruments alone.

8 Conclusion

Urban administrations worldwide are increasingly implementing *smart city* applications, ranging from traffic management to energy supply systems. The accompanying narrative consistently highlights their potential to improve the cities' sustainability, safety, and efficiency. Critical research, however, argues that the development of smart city applications is driven mainly by the economic interests of private companies, often sidelining citizens and their perspectives in planning and implementation. Recent studies also show how smart city technologies can exacerbate social inequality by mainly serving privileged groups.

Research on citizens' perceptions of smart city technologies is still relatively new. Most studies use qualitative approaches and focus on individual technologies. Our study adds to the field by investigating which distinct patterns underlie public attitudes toward smart city applications and how these patterns vary across social groups. Using a probability-based online panel in Germany, we surveyed 2021 respondents about their familiarity with and desirability of eleven smart city applications. Applying the bias-adjusted three-step latent class analysis, we identified two familiarity ("Self-declared novices" and "Self-declared insiders") and three desirability ("Cautious supporters," "Strong supporters," and "Reluctant skeptics") classes. We further found that sociodemographic characteristics such as gender, education, urbanicity, and household income are significantly associated with class membership.

Our study contributes to previous research by uncovering patterns in citizens' attitudes towards a wide range of smart city applications and by providing valuable insights for researchers and practitioners into the factors that shape these attitudes.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s00146-025-02815-8.

Acknowledgements We thank Sophia Piesch and the anonymous reviewer for their constructive comments on an earlier version of this paper. We are also grateful to our colleagues Frauke Kreuter, Christoph Kern, Heiner Stuckenschmidt, Kai Eckert, Frederic Gerdon, Jakob Kappenberger, and Florian Rupp for their collaboration on the CAIUS project. We especially thank Frederic Gerdon for his support in conceptualizing the survey.

Author contributions Conceptualization: DS and RB, Formal analysis: DS, Funding acquisition: RB, Methodology: DS, Validation: RB, Visualization: DS, Writing—original draft: DS, Writing—review & editing: DS and RB.

Funding Open Access funding enabled and organized by Projekt DEAL. Funding was provided by Volkswagen Foundation,"Consequences of Artificial Intelligence for Urban Societies (CAIUS)".

Data availability Data and R code are publicly available at https://osf.io/kvzfe/.

Declarations

Competing interests The authors declare no competing interests.

References

Angelidou M (2017) The role of smart city characteristics in the plans of fifteen cities. J Urban Technol 24(4):3–28. https://doi.org/10.1080/10630732.2017.1348880

Albino V, Berardi U, Dangelico RM (2015) Smart cities: definitions, dimensions, performance, and initiatives. J Urban Technol. https://doi.org/10.1080/10630732.2014.942092

Batty M (2024) The computable city: histories, technologies, stories. MIT Press, Predictions

Bhattacharya P (2025) Gendered mediations of urban life: the politics of 'space.' In: Cities: inclusive, liveable, and sustainable. Routledge

Bijker WE (2010) How is technology made?—that is the question! Camb J Econ 34(1):63–76

Cugurullo F (2018) The origin of the smart city imaginary: from the dawn of modernity to the eclipse of reason. In: The Routledge Companion to Urban Imaginaries, pp 113–24. Routledge

Cui Q, Zhang Y, Yang G, Huang Y, Chen Yu (2023) Analysing gender differences in the perceived safety from street view imagery. Int J Appl Earth Obs Geoinf 124:103537. https://doi.org/10.1016/j.jag.2023.103537

Engin Z, Treleaven P (2019) Algorithmic government: automating public services and supporting civil servants in using data science technologies. Comput J 62(3):448–460. https://doi.org/10.1093/comjnl/bxy082

Echebarria C, Barrutia JM, Aguado-Moralejo I (2021) The smart city journey: a systematic review and future research agenda. Innov Eur J Soc Sci Res 34(2):159–201. https://doi.org/10.1080/13511610.2020.1785277

Fairchild K (2023) Understanding street harassment as gendered violence: past, present, and future. Sex Cult 27(3):1140–1159. https://doi.org/10.1007/s12119-022-09998-y

Gough A (2016) The gendered city. In: Sustainability citizenship in cities. Routledge

Golubchikov O, Thornbush M (2020) Artificial intelligence and robotics in smart city strategies and planned smart development. Smart Cities 3(4):1133–1144. https://doi.org/10.3390/smartcities3040056

German S, Metternicht G, Laffan S, Hawken S (2023) Intelligent spatial technologies for gender inclusive urban environments in today's smart cities. In: Intelligent Environments, pp 285–322. North-Holland

Hartley K (2023) Public perceptions about smart cities: governance and quality-of-life in Hong Kong. Soc Indic Res 166(3):731–753. https://doi.org/10.1007/s11205-023-03087-9

Hartley K (2024) State-society relations and government technology: a survey of public awareness and communication in Hong Kong. Data Policy 6:e18. https://doi.org/10.1017/dap.2024.15

Hartley K, Aldag A (2024) Public trust and support for government technology: survey insights about Singapore's smart city policies. Cities 154:105368. https://doi.org/10.1016/j.cities.2024.105368

James P, Astoria R, Castor T, Hudspeth C, Olstinske D, Ward J (2020) Smart cities: fundamental concepts. In: Augusto, JC (ed.), Handbook of smart cities, pp 1–26. Springer International Publishing, Cham

Joss S, Sengers F, Schraven D, Caprotti F, Dayot Y (2019) The smart city as global discourse: storylines and critical junctures across 27 cities. J Urban Technol 26(1):3–34. https://doi.org/10.1080/10630732.2018.1558387

Kintzi K (2024) The smart grid archipelago: infrastructures of networked (dis)connectivity in Amman. Environ Plann D: Soc Space 42(4):492–511. https://doi.org/10.1177/02637758231209656

Kaharevic A, Wihlborg E (2024) Whose future is smart?: a systematic literature review of smart cities and disadvantaged neighborhoods. In: Proceedings of the 17th international conference on theory and practice of electronic governance, ICEGOV '24, pp 318–26. Association for Computing Machinery, New York, NY, USA

Kitchin R, Cardullo P, Di Feliciantonio C (2019) Citizenship, justice, and the right to the smart city. In: Cardullo P, Di Feliciantonio C, Kitchin R (eds), The right to the smart city, pp 1–24. Emerald Publishing Limited

Lindner C, Meissner M (eds) (2018) The Routledge companion to urban imaginaries. Routledge, London

Magidson J, Vermunt JK (2004) Latent class models. In: Kaplan D (ed.) The SAGE handbook of quantitative methodology for the social sciences, pp 175–98. SAGE Publications, Thousand Oaks, California

McElroy E, Vergerio M (2022) Automating gentrification: landlord technologies and housing justice organizing in New York City homes. Environ Plann D Soc Space 40(4):607–626. https://doi.org/10.1177/02637758221088868

Maalsen S, Wolifson P, Dowling R (2023) Gender in the Australian innovation ecosystem: planning smart cities for men. Gend Place Cult 30(2):299–320. https://doi.org/10.1080/0966369X.2022.2053068

Nieuwenhuijsen MJ (2024) Climate crisis, cities, and health. Lancet 404(10463):1693–1700. https://doi.org/10.1016/S0140-6736(24)01934-2

Osipova M, Hornecker E (2023) Exploring the potential for smart city technology for women's safety. In: Proceedings of the 26th international academic Mindtrek conference, Mindtrek '23, pp 245–256. Association for Computing Machinery, New York, NY, USA

Oberascher M, Rauch W, Sitzenfrei R (2022) Towards a smart water city: a comprehensive review of applications, data requirements, and communication technologies for integrated management. Sustain Cities Soc 76:103442. https://doi.org/10.1016/j.scs.2021.103442

Phillips A, Canters F, Khan AZ (2022) Analyzing spatial inequalities in use and experience of urban green spaces. Urban for Urban Green 74:127674. https://doi.org/10.1016/j.ufug.2022.127674

R Core Team (2025) R: a language and environment for statistical computing

Rathore M, Mazhar M, Anand P, Seungmin R, Murad K, S. V, Syed AS (2021) Smart traffic control: identifying driving-violations using fog devices with vehicular cameras in smart cities. Sustain Cities Soc 71:102986. https://doi.org/10.1016/j.scs.2021.102986

Shelton T, Zook M, Wiig A (2015) The 'actually existing smart city.' Camb J Reg Econ Soc 8(1):13–25. https://doi.org/10.1093/cjres/rsu026

Sadowski J, Bendor R (2019) Selling smartness: corporate narratives and the smart city as a sociotechnical imaginary. Sci Technol Hum Values 44(3):540–563. https://doi.org/10.1177/0162243918806061

Shadowe, N, Lodato T, Loi D (2020) Participatory governance in smart cities: future scenarios and opportunities. In: Streitz N, Konomi S (eds), Distributed, ambient and pervasive interactions, pp 443–463. Springer International Publishing, Cham

Spicer Z, Goodman N, Wolfe DA (2023) How 'smart' are smart cities? Resident attitudes towards smart city design. Cities 141:104442. https://doi.org/10.1016/j.cities.2023.104442

van Twist A, Ruijer E, Meijer A (2023) Smart cities & citizen discontent: a systematic review of the literature. Gov Inf Q 40(2):101799. https://doi.org/10.1016/j.giq.2022.101799

Vanolo A (2014) Smartmentality: the smart city as disciplinary strategy. Urban Stud 51(5):883–898. https://doi.org/10.1177/0042098013494427

Vermunt JK (2010) Latent class modeling with covariates: two improved three-step approaches. Polit Anal 18(4):450–469. https://doi.org/10.1093/pan/mpq025

Valentine G (2025) Age inequality: geography's overlooked dimension of difference. In: Progress in human geography, 03091325251398859. https://doi.org/10.1177/03091325251398859

Vermunt JK, Magidson J (2025) "LG-syntax user's guide: manual for LatentGOLD syntax module version 6.1"

van Ham M, Tammaru T, Ubarevičienė R, Janssen H (eds) (2021) Urban socio-economic segregation and income inequality: a global perspective. Springer Nature

Winner L (2007) Do artifacts have politics?. In: Computer ethics. Routledge

Xu F, Wang Qi, Moro E, Chen L, Miranda AS, González MC, Tizzoni M, Song C, Ratti C, Bettencourt L, Li Y, Evans J (2025) Using human mobility data to quantify experienced urban inequalities. Nat Hum Behav 9(4):654–664. https://doi.org/10.1038/s41562-024-02079-0

Yarker S (2021) A research agenda for geographies of everyday intergenerational encounter. Area 53(2):264–271. https://doi.org/10.1111/area.12716

Zubizarreta I, Seravalli A, Arrizabalaga S (2016) Smart city concept: what it is and what it should be. J Urban Plann Dev 142(1):04015005. https://doi.org/10.1061/(ASCE)UP.1943-5444.0000282