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AI on the street: Context-dependent responses to artificial intelligence

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ABSTRACT

As artificial intelligence (AI) applications proliferate, their creators seemingly anticipate that users will make similar trade-offs between costs and benefits across various commercial and public applications, due to the technological similarity of the provided solutions. With a multimethod investigation, this study reveals instead that users develop idiosyncratic evaluations of benefits and costs depending on the context of AI implementation. In particular, the tensions that drive AI adoption depend on perceived personal costs and choice autonomy relative to the perceived (personal vs. societal) benefits. The tension between being served rather than exploited is lowest for public AI directed at infrastructure (cf. commercial AI), due to lower perceived costs. Surveillance AI evaluations are driven by fears beyond mere privacy breaches, which overcome the societal and safety benefits. Privacy-breaching applications are more acceptable when public entities implement them (cf. commercial). The authors provide guidelines for public policy and AI practitioners, based on how consumers trade off solutions that differ in their benefits, costs, data transparency, and privacy enhancements.

1. Introduction

In the next five years, 60% of people worldwide can expect profound changes to their daily life due to artificial intelligence (AI) (World Economic Forum, 2022). Applications of AI underlie algorithms that are used to search for information, learn a new language and skills, shop for products and services, or interact with appliances (Davenport et al., 2020). But beyond the plethora of applications by commercial entities, AI also appears increasingly in use in the public sector, where government and public officials rely on it to provide services such as e-government, healthcare, and education (Kushchu & Kuscu, 2003) or to empower public infrastructure, like traffic control and waste management (McKinsey, 2018). Global investments in smart cities are anticipated to reach US$2.51 trillion by 2025 (Feltes, 2021).

As AI proliferates, it becomes paramount to understand how people evaluate its diverse applications across the contexts in which it gets implemented. For example, a person may readily interact with a virtual assistant (e.g., Alexa) to order plane tickets but hesitate to use a virtual assistant at a government administration office issuing visa documents. Why this person would express divergent AI evaluations across these contexts is unclear though. Context-dependent evaluations may encompass not only the specific AI application but also the setting and perceived purpose for which it gets implemented. Notably,

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empirical evidence about drivers of citizens' AI evaluations in public sector settings is scarce (Zuiderwijk et al., 2021). In general, we know little about how citizens evaluate diverse public-sector AI applications, such as public administration chatbots versus smart traffic lights versus air quality monitoring (Lam & Ma, 2019; Wirtz et al., 2019). Moreover, only scarce evidence is available regarding differences across commercial and public contexts: consumers may willingly adopt biometric face scanning or fingerprint access for their personal devices (Minsky, 2019) but reject police uses of such biometrics (Madiega & Mildebrath, 2021; Minsky 2019). However, we lack clear insights into whether such context dependences reflect the entity that implements it (e.g., government versus commercial sector) or perceptions of the purposes of the specific AI application (e.g., traffic monitoring versus air quality monitoring). Such considerations reflect real-world developments. For example, smart streetlights and traffic sensors might optimize energy consumption and track criminal activity, but they also can monitor people's movement and record videos of the area (Ray, 2020). Most people likely develop different evaluations of AI directed at improving public infrastructure versus surveilling their movements (van Zoonen, 2016). Noting the lack of research and evidence-based support, both regulators (European Commission, 2021) and researchers have called for more research on the drivers, barriers, impacts, and unforeseen consequences underlying various AI implementations (Agarwal, 2018; Tangi et al., 2022).

To address these gaps, we explore people's evaluations of the perceived benefits and costs of AI applications across diverse contexts, in which they function as consumers or users of commercial and public AI applications. Such perceived benefits and costs likely drive the adoption of and support for the implementation of any particular AI application (Fox et al., 2021; Puntoni et al., 2021; Venkatesh & Davis, 2000). That is, people evaluate specific AI applications according to the extent to which they *serve them* with perceived benefits like efficiency or personalization, as well as the extent to which they *exploit them* by imposing perceived costs related to privacy, civil freedoms, or job losses (Puntoni et al., 2021). Instead of exploring benefits and costs in isolation, as is common in prior literature, we seek to evaluate AI applications on the basis of the *tensions* that people perceive between benefits and costs in *specific contexts* (Puntoni et al., 2021). In turn, we can determine how people evaluate different AI applications and what drives their support for or reactance to AI across contexts (Mick & Fournier; 1998; Nissenbaum, 2009). Accordingly, we consider two main research questions:

- What tensions and trade-offs do citizens perceive when adopting AI in public contexts?
- How does the broad context of AI implementation affect evaluations of benefits and costs, and thus willingness to adopt an AI application?

To address these questions, we adopt a multimethod approach (survey, regression, experiment, and choice-based conjoint) and explore citizens' evaluations of AI across multiple contexts. Specifically, we include common AI applications in commercial contexts (e.g., home assistants, chatbots) but also various public context AI applications directed at either infrastructure (e.g., waste management) or the community (e.g., public surveillance). In Studies 1a and 1b, we explore how people evaluate AI applications in 21 different contexts, to establish a foundational understanding of contextual differences, sources of tensions, and their impacts on people's willingness to adopt AI applications. With a controlled experimental design, in Study 2, we explore how contextual effects affect evaluations of the *same* technology (e.g., commercial versus public application of smart camera video surveillance). Thus we can distinguish the effects of the technology from the impact of the entity that implements it or context in which it gets implemented. Finally, with Study 3 we explore trade-offs in a choice-based conjoint study, in which respondents choose their preferred AI solutions in different contexts that vary on multiple dimensions (technology, benefits, costs, control, AI agency, data transparency, and type of user holding the data).

The combined findings establish three key contributions. First, for marketing and AI literature, we provide empirical evidence of how the context affects customers' AI evaluations and the impact of the tensions between being served and being exploited for diverse AI applications (Grewal et al., 2021; Puntoni et al., 2021). These tensions depend on whether an AI implementation is perceived as directed toward personal benefits or societal benefits, as well as the extent to which it affects perceived levels of autonomy/control. Notably, feeling served, rather than exploited, reaches the highest level for AI applications that exhibit societal rather than personal benefits and costs (e.g., air quality monitoring); support for their adoption is greater than that for familiar commercial applications in the public sector (e.g., chatbots). Second, related to privacy literature, we show that AI-related fears extend beyond privacy concerns, suggesting the need for more insights into the amplifying effects of different perceived costs. For AI applications that evoke strong risks to privacy or civil freedoms, government implementation is preferred over commercial versions, particularly if the data collection and ownership are very transparent. Third, for public policy makers, we provide guidelines for when to deploy AI in public settings. In contrasting the tensions that arise for AI implementation across public and commercial sectors (Manzoni et al., 2021), we reveal the potential for privacy-enhancing solutions (e.g., anonymization), data transparency, ownership, and benefit communication to increase citizens' adoption of AI solutions.

In the next section, we provide our theoretical conceptualization of context dependency in AI evaluations. This conceptualization informs our four propositions. Next, we present our multimethod studies, which test the elements of our theoretical conceptualization. Finally, we conclude this article with a discussion of the findings and their policy implications.

2. Theoretical conceptualization of context-dependent AI evaluations

An *AI application* can refer to diverse algorithms, systems, and devices that have capabilities for gaining insights, learning from data, and making informed decisions (Davenport et al., 2020). For simplicity, we define *public AI* as any AI applications in the public sector directed toward public administration or the infrastructure and implemented by public entities like governmental agencies or local municipalities. Then we define *commercial AI* as those AI applications implemented by commercial entities (firms), typically directed toward personal use (e.g., virtual assistants like Alexa, wearable devices). Before they adopt unknown, sophisticated technologies that surpass human cognitive and physical capabilities, users must make a leap of faith and trust processes that cannot be directly observed or controlled (Glikson & Woolley, 2020). Trust can stem from the presence and confirmation of norms that govern expectations, roles, and reactions. But such norms vary across the contexts that constitute people's lived experiences (Nissenbaum, 2009). Acceptable practices in commercial AI for personal use may evoke reactance in public AI applications (Wirtz et al., 2020).

However, empirical explanations of these differences are scarce, mostly conceptual, and usually focused on the benefits of AI for efficient data analysis and flow or else the ethical challenges it raises (Lam & Ma, 2019; Wirtz et al., 2019; Zuiderwijk et al., 2021). Available evidence also is based on case studies of pilot projects or small-scale surveys of self-selected citizens (Gutiérrez et al., 2016; Tangi et al., 2022; van Eijk & Steen, 2016). We thus lack sufficient understanding of the technological, ethical, and societal challenges that affect the implementation and integration of AI in public administration efforts (Welby, 2019; Wirtz et al., 2019, 2020). Furthermore, few governments have established legislative regulations to define responsible, human-centric implementation boundaries (Manzoni et al. 2022; Shearer et al., 2020). Rather than an in-depth understanding of citizens' trade-offs, public AI implementations often reflect political agendas (Cugurullo, 2016), local officials' personal experiences (Horowitz & Kahn, 2021), or the mindsets of AI designers, who tend to regard AI as a neutral tool that can be applied across contexts to increase data processing efficiency and reduce administrative costs (Fatima et al., 2020; Godfrey, 2019; Sun & Medaglia, 2018).

Yet essential differences inherently limit the generalizability of findings from commercial AI evaluations to public sector AI applications. Compared with the relatively simple heuristics consumers use to evaluate products for private use, evaluating public AI is more cognitively taxing. Citizens must evaluate multiple benefits and costs that vary on different personal and societal dimensions (Luce et al., 1999; van Eijk & Steen, 2016). The perceived benefits and costs derive from the purpose of the AI application, such that even for public AI applications, people might differentiate applications that offer *personal benefits* (e.g., chatbots that help citizens interact with public administrations) from those that offer primarily *societal benefits* for the public infrastructure or community (e.g., air quality monitoring that measures levels of pollution in a neighborhood). Societal benefits such as environmental protection, public safety, public health, and infrastructure improvements are more ambiguous, emotion-laden, and less personally gratifying than personal benefits sought from commercial AI (Acquisti et al., 2020; Fatima et al., 2020). Moreover, societal benefits require considering multiple stakeholders whose interests and even definitions of the goals of public AI implementation could conflict (Desouza et al., 2020; Sun & Medaglia, 2019; Zuzul, 2019). It is more complex to evaluate benefits against costs in contexts that involve moral dimensions of fairness, justice, equality, or transparency (Bigman & Gray, 2018; Wirtz et al., 2019).

Notably, perceived costs include both monetary and non-monetary elements, such as privacy concerns or choice autonomy (André et al., 2018; Botti et al., 2023; Martin & Murphy, 2017). Public AI may evoke fewer monetary cost considerations, relative to commercial AI, but it likely raises more concerns about privacy, surveillance, slippery slopes, or threats to personal freedom (Cave et al., 2019; Drobotowicz et al, 2021; Hartzog & Selinger, 2015). Public AI applications might diminish users' autonomy because citizens must "surrender" personal information (Walker, 2016; Wertenbroch et al., 2020). *Autonomy* implies free will, self-determination, and the person's "ability to make and enact decisions on their own, free from external influences imposed by other agents" (Wertenbroch et al., 2020, p. 430). Whether people feel vulnerable to such threats depends on their individual perceptions of control over their personal data and the outcomes of AI processes (Ackerman et al., 2022; André et al., 2018; Martin & Murphy, 2017). Intense privacy concerns decrease firm evaluations, trust, data disclosures, purchases, and post-purchase behaviors, whereas they increase risk perceptions and protective behaviors (Acquisti et al., 2015; Martin & Murphy, 2017). Such concerns also reflect the perceived sensitivity of the data, such that if captured data are highly sensitive, perceived risk creates stronger reactance (Okazaki et al., 2020; van Zoonen, 2016). These diverse costs may create a feeling of being exploited, relative to the feeling of being served by the perceived benefits of a public AI application (Puntoni et al., 2021).

In summary, we anticipate that contextual differences in AI evaluations manifest along two axes: the perceived benefits of AI (personal and societal) and the costs of being exploited (autonomy in choice, as a level of control over personal costs). On the basis of these perceived benefit and cost dimensions, we group diverse public and commercial AI applications into the four categories in Fig. 1: commercial-like, surveillance, social personal, and social impersonal AI. Within each category, citizens encounter tensions between being served and being exploited, which they address by assigning idiosyncratic weights to the perceived costs and benefits of a specific AI application in the broader context of its implementation. We advance a set of propositions based on this conceptual reasoning.

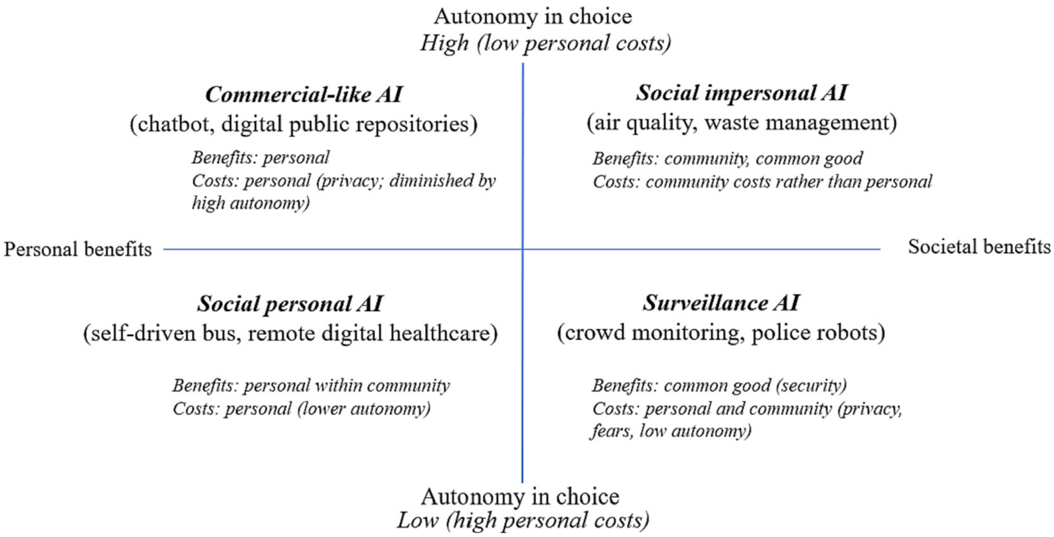

Fig. 1. Benefit versus cost dimensions in AI evaluations.

2.1. Commercial-like AI

In the commercial-like AI category, we include applications directed toward personal benefits with relatively high choice autonomy (e.g., chatbots). In commercial contexts, people use technology to achieve active personal goals (shopping, finding information, connecting with others; Oyserman & Schwarz, 2020), and their evaluations primarily focus on personal gains, such as perceived usefulness, increased efficiency, and ease of use (Venkatesh & Davis, 2000). Due to their familiarity with similar applications in commercial contexts, citizens likely develop similar basic expectations for equivalent public applications, which is why we call this category "commercial-like." For example, users of AI-based virtual assistants in public administration report appreciation for the positive personalization, time efficiency, and sensory stimulation they gain (Chen et al., 2021). Familiarity also likely increases perceived autonomy. A stronger sense of control and choice autonomy prompts positive attributions and self-attributions of success, which affect trade-offs in favor of benefits and lower the salience of costs (André et al., 2018; Wertenbroch et al., 2020).

The costs in commercial-like applications, in terms of privacy harms and autonomy, are intangible, difficult to isolate and quantify, distant, and delayed, so people tend to undervalue them (Acquisti et al., 2020; Zuboff, 2019). Publicly available data can expose people's identity, social security numbers (Acquisti & Gross, 2009), indirect social connections (Crandall et al., 2010), sexual orientation (Wang & Kosinski, 2018), or political orientation (Kosinski, 2021). However, in commercial contexts, the direct, personal benefits become more salient than concerns about the use of personal data (Oyserman & Schwarz, 2020). Therefore, in commercial-like AI applications, the feeling of being served should dominate over concerns about being exploited (Acquisti et al., 2020). Similar trade-offs of benefits and costs likely arise when citizens evaluate commercial-like applications in the public sector, so we propose:

P1a: In commercial-like AI contexts, the perceived personal benefits of being served outweigh the perceived costs of being exploited.
P1b: In commercial-like AI contexts, personal benefits have a stronger influence than social benefits on support for and adoption of public AI applications.

2.2. Surveillance AI

Diametrically opposite from commercial-like AI, we define surveillance AI applications as characterized by stronger societal than personal benefits and high personal costs of autonomy. Surveillance AI involves the "systematic collection and analysis of personal information in the population for purposes of influence, management, protection, or direction" (Lyon, 2007, p. 14). Common applications include smart CCTV crowd surveillance, sound-of-movements monitoring, or the use of police robots (Newell et al., 2018; Ray, 2020). A primary benefit of surveillance technologies is to increase safety or public security (Brockdorff et al., 2013). These societal benefits clash with personal freedoms though, because they tend to require privacy infringements, loss of autonomy, limited access to social systems, and threats of discrimination or bias (Desouza et al., 2020; Nam, 2021). Evaluations of surveillance AI feature substantial emotional complexity. The risks and costs tend to be personal and overemphasized, relative to the collective, distant, and less immediate benefits of public safety (Degli Esposti et al., 2021; Luce et al., 1999). In a survey of U.S. citizens, only 39% agreed with the U.S. government monitoring

U.S. citizens; that percentage rose to 56% for monitoring foreign citizens, 60% for U.S. leaders, 62% for foreign leaders, and 89% for suspected terrorists (Nam, 2019). People only accept surveillance applications in contexts marked by threats, such that a greater perceived need for safety justifies the sacrifice of their rights to privacy (Hartzog & Selinger, 2015; van Heek et al., 2016). In private spaces, where perceived safety is higher, protection may seem less relevant, so the need for privacy dominates (Sanquist et al., 2008; van Heek et al., 2016). Consequently, surveillance implemented in what is perceived as private space is evaluated not in terms of safety benefits but rather as an unacceptable breach of private space (Brockdorff et al., 2013; Nam, 2019). Surveillance AI may be more accepted in public contexts (implemented by public entities) than in commercial contexts (implemented by firms).

Existing literature rarely distinguishes privacy concerns from other fears (e.g., government intrusion, surveillance fears; Dinev et al., 2008; Nam, 2019). Perceived government intrusiveness has an inverse relationship with the perceived effectiveness of a system (Sanquist et al., 2008) and can deter new technology adoption (Dinev et al., 2008). Such fears get exacerbated by the so-called slippery slope—namely, the belief that accepting some forms of technology surveillance might lead legislators, voters, or judges to impose ever stronger surveillance policies (Volokh, 2003). Dread of a "catastrophic potential" and fear of the unknown (Slovic et al., 1981) can be exacerbated by the implicit bias of AI applications, which reflect human biases (Wirtz et al., 2020). For example, facial recognition technology can predict political orientations based on facial images, which could result in civil rights infringements (Kosinski, 2021). As Brayne (2017) finds, uses of surveillance AI by U.S. law enforcement agencies have exacerbated social inequalities and discrimination disproportionally against citizens previously convicted of crimes, because the predictive algorithms identify these citizens more readily, leading to more frequent stops that, in turn, increase their personal risk score in the AI system. Laypeople are particularly averse to allowing machines to make moral judgments in public contexts that raise moral dilemmas, like determining parole for offenders or choosing health treatments (Bigman & Gray, 2018). In these contexts, users believe that AI cannot account for uncertainty (Dietvorst & Bharti, 2020; Grove & Meehl, 1996), personal uniqueness (Longoni et al., 2019), empathy (Grove & Meehl, 1996), or procedural justice (Nagtegaal, 2021) to the same extent that humans can.

In summary, we predict that citizens undervalue the benefits of surveillance AI (to serve them), due to their lower personal attribution, and emphasize the potential costs (feeling exploited). Because governments are bound by accountability and proportionality requirements, these contextual effects should make surveillance more acceptable in public relative to commercial applications. We propose:

P2a: In surveillance AI contexts, the costs of being exploited outweigh the benefits of being served.
P2b: Surveillance AI applications receive greater support in public contexts compared with commercial contexts, especially when the perceived societal benefits are greater.

2.3. Social personal AI applications

Social personal AI include public AI applications directed toward the community rather than the infrastructure. They offer personal benefits to community members. For example, autonomous vehicles for public transport (self-driven buses) or digital access to health services in remote areas represent meaningful public services that provide direct personal benefits to users (McKinsey, 2018; Wirtz et al., 2019). By equipping hospitals with remote-controlled robots, the Avatar Kids project helps hospitalized children maintain a virtual presence in their classrooms (Taddeo & Floridi, 2018). The evaluations of the benefits in this case may be similar to those for commercial-like AI. However, social personal AI offers less (perceived) personal choice autonomy, due to the communal context of these AI implementations. Still, the perceived benefits should surpass the personal costs of privacy and autonomy, and fears should be less prominent, relative to those evoked by surveillance AI. For example, perceptions of health and societal benefits drove adoption of the COVID-19 tracker app in Ireland, and privacy concerns did not appear to influence acceptance, either pre- or post-launch (Fox et al., 2021). Thus, we propose:

P3a: In social personal AI contexts, the perceived benefits of being served outweigh the perceived costs of being exploited, but to a lesser extent than in commercial-like AI contexts due to diminished choice autonomy.
P3b: In social personal AI contexts, adoption of and support for AI are driven primarily by personal rather than social benefits, but the influence of personal benefits on adoption is relatively weaker than in commercial-like AI contexts.

2.4. Social impersonal AI

Finally, this category of public AI aims for societal benefits, which typically entail low personal costs, because they are directed at public infrastructure. Examples include smart traffic lights that improve traffic flows, optimizing electricity use in public buildings, or using AI image recognition of past earthquakes to predict new ones (Furumura et al., 2020; McKinsey, 2018). The benefits usually pertain to improvements in the costs and efficiency of public infrastructure, with limited personal gratification. For example, for smart electrical grids, perceived behavioral control and attitudes toward energy savings are powerful determinants of adoption (Perri et al., 2020). In some contexts, these infrastructure-directed benefits may be appreciated more than personally directed ones. In Japan, public AI applications are trusted more when they offer waste sorting advice rather than parenting (i.e., personal) advice (Aoki, 2020).

Yet because they (seemingly) do not involve personal data collection, the perceived feeling of being exploited could be lowest for social impersonal AI. Citizens simply might not be aware that their personal information can be collected by public infrastructure sensors (e.g., smart traffic lights) (Ray, 2020). The perception of low privacy costs should increase trust and diminish predictions of harm (van Zoonen, 2016). Familiarity in this context may have a significant influence too. In this category, applications by commercial entities are rare. A survey of 690 U.S. local officials revealed their greater support for autonomous vehicles rather than autonomous surgeries, depending on their prior familiarity with AI implementation and their level of concern about privacy, bias in algorithms, and transparency (Horowitz & Kahn, 2021), such that it appears to reflect the infrastructure- versus person-oriented context of the AI implementation. In conclusion, social impersonal AI applications likely evoke perceptions of little exploitation but relatively high benefits to society.

P4a: In social impersonal AI contexts, tensions between being served and exploited are minimized, due to the low perceptions of feeling exploited.
P4b: In social impersonal AI contexts, support for and adoption of AI are primarily driven by the social benefits they provide, rather than the personal benefits.

2.5. Moderating effects of data transparency and ownership

Support for AI implementation depends on how the data are collected and people's trust in and familiarity with the agent that deals with those data, particularly in contexts that entail high personal costs (Degli Esposti et al., 2021; Struminskaya et al. 2020). Public AI applications are subject to more stringent transparency standards than those introduced by firms (Desouza et al., 2020), so privacy breaches in commercial applications may be more prevalent than in government applications. Dinev and colleagues (2008) show that in online commercial settings, government intrusion is less salient than are corporate intrusions of privacy. Moreover, privacy risk perceptions are lower when the entity collecting the data is the government, particularly in conditions marked by low perceived control over personal information (Xu et al., 2012). According to an evaluation of tracking performed by cookies across 2000 high-traffic websites, government pages engage in the least tracking, prompt fewer opt-out breaches, and offer more readable privacy policies than commercial or entertainment websites (Sanchez-Rola et al., 2019). We therefore anticipate that *data ownership* (e.g., government vs. commercial owner) and *transparency of data use* (e.g., collecting or anonymizing personal data) inform the creation of public AI solutions. Without access to prior evidence, we adopt an exploratory approach to understand how those regulatory tools affect support for AI implementations across diverse contexts (e.g., public, semi-public, commercial).

3. Overview of studies

Because citizens' judgments of and decisions about public AI solutions are likely complex and multifaceted, we take a multimethod approach. In Studies 1a and 1b, we explore how evaluations of costs and benefits and adoption intentions differ across AI implementation contexts. To test our conceptual reasoning, we include a wide range of contexts that differ in their setting and purpose (i.e., commercial vs. public sector; directed toward personal benefits, community, or infrastructure). In Study 1b, we also explore how tensions between benefits and costs affect citizens' willingness to support AI applications across the four categories of contexts in Fig. 1 (i.e., along the dimensions of personal vs. societal benefits and low vs. high choice autonomy). Then, in Study 2, using an experimental approach, we analyze how public versus commercial settings for implementing the same AI technology affect evaluations of benefits and costs and their tensions. With this evidence, we can tease apart the effects of the entity implementing the AI from the differences across AI applications. Finally, in Study 3, with a choice-based conjoint design, we explore individual trade-offs between AI solutions that differ in terms of the technology, the entity implementing the solution, benefits, costs, control/data transparency, and AI agency.

4. Study 1: Differences in AI evaluations across public AI contexts

4.1. Study 1a

To identify diverse contexts of AI application, we mapped the most prominent applications used in public and commercial settings, according to a broad review of AI literature and McKinsey's (2018) classification of AI categories implemented in public contexts. We provided participants with concrete descriptions and images of 21 AI implementation contexts (see Appendix A), rather than asking about their feelings about AI in general, in line with evidence showing that laypeople lack a clear understanding of AI (Cave et al., 2019). The participants randomly evaluated 3 AI applications on 21 dimensions, identified from prior literature as drivers of AI adoption. At the end of the survey, they also provided demographic information (see the Supplementary Web Appendix, Table W1, for the descriptive statistics and measures). We ran five rounds of data collection, using the same design on the Prolific academic platform, over the course of about a year (to account for potential effects of the COVID-19 pandemic), in December 2019 (N = 711), March 2020 (N = 803), April 2020 (N = 1003), June 2020 (N = 1011), and November 2020 (N = 999). Participants received monetary compensation of around $2. The average response time for each round was 15 min. Pairwise comparisons across the five rounds showed no significant trends or differences in the likelihood of adoption over time ($F(4, 4250) = 1.369$, $p = .242$). This finding in itself provides an interesting insight: AI evaluations are deeply rooted in stable evaluations of costs and benefits. The final pooled sample contains 4523 respondents who successfully completed the survey and attention checks.

4.1.1. Measures

With 21 attitudinal and behavioral measures, we capture participants' evaluations of the benefits, costs, and tensions associated with 21 contexts of AI applications (see Appendix A). The evaluated attributes, item scales, factor loadings, reliability statistics, and sources are available in the Supplementary Web Appendix (Table W2). To gauge the main constructs in our theoretical framework (personal benefits, societal benefits, and autonomy costs), we performed a principal component analysis with Varimax rotation. The Kaiser-Meyer-Olkin test of sampling adequacy equals 0.887, indicating that the sample is sufficient for factor analysis. Bartlett's test of sphericity is significant ($\chi^2(120) = 62109.29$, $p = .000$). The results yield three factors that account for 52.88% of the variance in the data (personal benefits, societal benefits, and perceived costs). Constructs show acceptable reliability scores with Cronbach α scores around and above 0.7. For theoretical purposes, we keep all the items, while acknowledging that some societal benefits items have lower factor loadings (e.g., 0.455 for social cohesion). The personal benefits comprise efficiency gains, ease of use, and perceived usefulness and helpfulness. The societal benefits are safety improvements, benefits to society, environment, social cohesion and social inequality reduction. The perceived costs factor includes fears of harm, privacy concerns, and job loss.

4.1.2. Results: Contextual differences in willingness to support an AI application

The results (Fig. 2) indicate substantial differences in respondents' willingness to support the implementation of an AI application, depending on the context (setting in which the AI is implemented). The participants expressed the highest willingness to support public infrastructure applications (e.g., natural disaster or air-quality monitoring). The AI applications that monitor infectious disease spreads and wearable devices both exhibit acceptance levels near the grand mean level. Surveillance applications and robots evoke much lower levels of support (mean of 3.3 out for 7 for surveillance AI and police robots). Common commercial AI applications like chatbots and delivery drones prompt evaluations below the grand mean.

4.2. Testing the theoretical framework and drivers of AI evaluations

To explore how evaluations of AI applications reflect the diverse attributes of AI, we also conducted a multidimensional preference analysis (Carroll & Arabie, 1998). Thus, we can map the relationships among the attributes on which the AI applications are evaluated and the positioning of each application relative to those attributes on a perceptual map, as in Fig. 3. The first two dimensions explain 65.5% of the variance in the data.

In support of our conceptual framework, Fig. 3 shows that respondents evaluate diverse application contexts differently on attributes related to the personal and societal benefits and costs of AI. Commercial-like applications cluster in the lower-left corner, scoring high on perceived personal benefits like efficiency, usefulness, and ease of use; they also are characterized by a high level of personal control (i.e., low autonomy costs). In this category, we find applications like smart home assistants, delivery drones, wearables, or service chatbots, as are often used in commercial contexts and applied in public contexts for similar purposes. In the upper right corner, the cluster of social impersonal attributes are perceived to benefit society and increase environmental benefits, safety, and overall quality of life; these applications include disaster monitoring, air quality controls, or water management. The social attributes relate negatively to privacy concerns and fears, which categorize the third segment in the map, or surveillance AI (e.g., face recognition, police robots, healthcare robots). Finally, a cluster of applications with characteristics that we have defined as social personal AI (e.g., self-driving busses, remote patient monitoring, local apps) are positively evaluated on ease of use and helpfulness and, to some extent, improving the quality of life. These findings offer initial support for our conceptual categorization of AI based on perceived benefits and costs.

We also can group the 21 contexts into the four categories in Fig. 1. The category membership assignments are in Appendix A, which also provides descriptions of each AI application context.

4.2.1. Choice autonomy dimension

We run three one-way analyses of variance (ANOVAs) using Bonferroni's test to gauge differences across the four AI context categories with respect to choice autonomy ($F(3,4250) = 253.601$, $p < .001$). In line with our theorizing, the social impersonal AI and commercial-like AI display the highest levels of perceived autonomy ($M_{SI} = 61.86$, $SD = 30.94$; $M_C = 61.79$, $SD = 28.91$). The social personal AI and surveillance AI prompt lower autonomy perceptions ($M_{SP} = 58.25$, $SD = 29.83$; $M_S = 42.61$, $SD = 31.93$) ($F(3,4250) = 253.601$, $p < .001$).

4.2.2. Personal and societal benefits

The analyses of differences in personal benefits ($F(3, 4250) = 910.562$, $p < .001$) and societal benefits ($F(3, 4250) = 311.857$, $p < .001$) also reveal significant distinctions across the four categories. Participants report the most personal benefits from commercial-like AI ($M_C = 4.95$, $SD = 0.96$) but also the lowest perceptions of societal benefits ($M_C = 3.92$, $SD = 0.98$). Social personal AI scores higher on personal than societal benefits ($M_{SP} = 4.58$, $SD = 1.02$; $M_{SP} = 4.36$, $SD = 1.02$, respectively), and social impersonal AI indicates higher levels of societal benefits versus personal benefits ($M_{SI} = 4.62$, $SD = 0.98$; $M_{SI} = 4.40$,

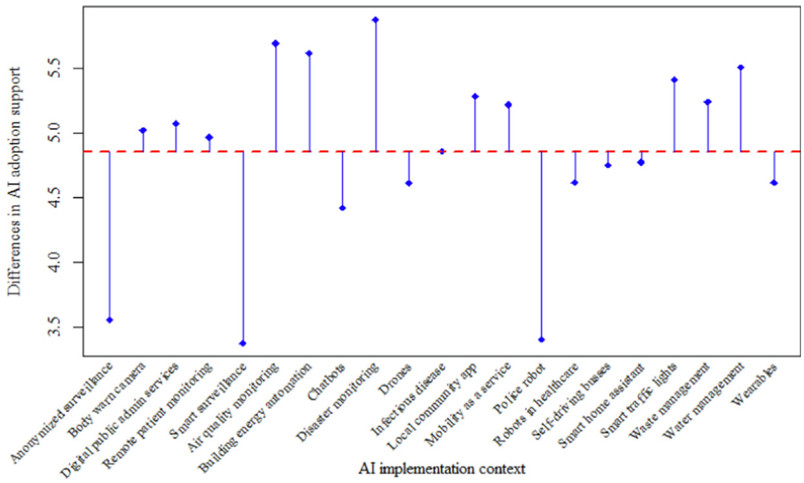

Fig. 2. Differences in willingness to support AI across implementation contexts. Notes: The figure depicts the average evaluations of 21 AI contexts by 4,523 respondents, according to composite scores of their responses to the questions: "If I had a choice, I would adopt this technology" and "I would support policies that would implement this technology" (1 = "Completely disagree," 7 = "Completely agree"). The grand mean (red dotted line) represents average adoption propensity across contexts, M = 4.83 (SD = 0.71). The Y axis and vertical blue lines represent the difference in average adoption/support intentions relative to this grand mean. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

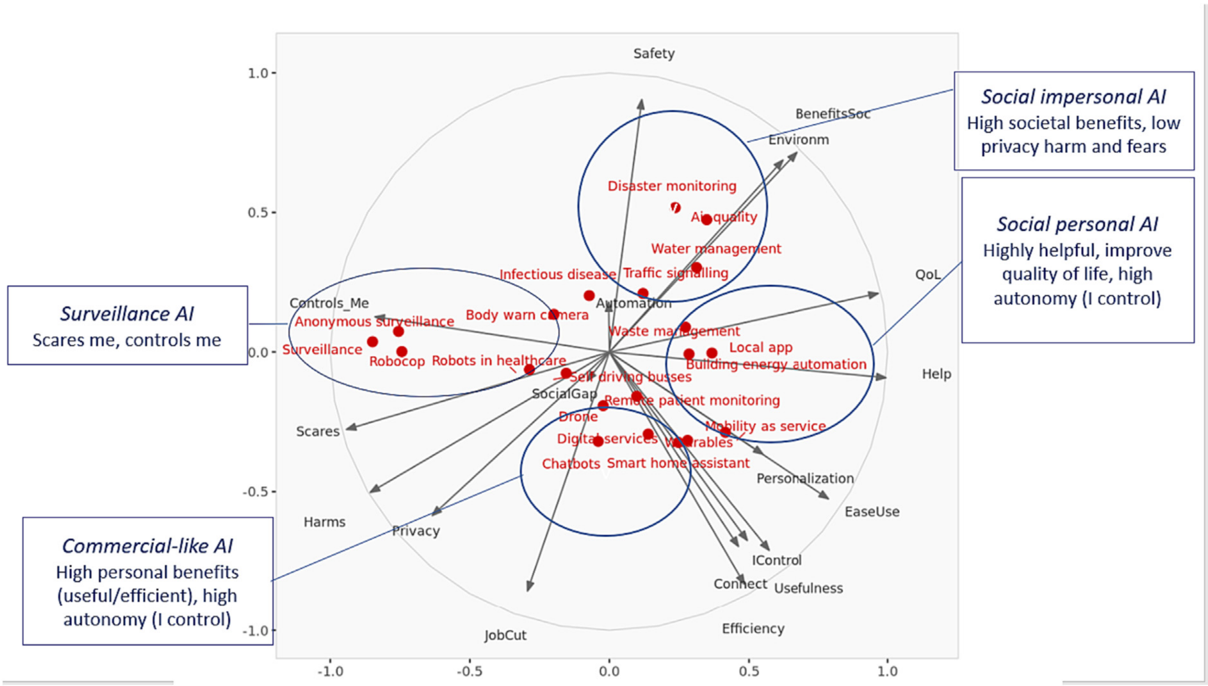

Fig. 3. Perceptual map of attributes of AI evaluations. Notes: This figure shows the results of a multidimensional preference analysis across evaluation attributes (vectors) and positioning of AI applications along those attributes (dots). The length of vectors (attributes) is proportional to the variance they explain. The attributes whose vectors are close are highly correlated; perpendicular attributes are uncorrelated; and those in opposite directions are negatively correlated. The further way from the center, the higher an application scores on that dimension (Lilien et al., 2017).

SD = 0.09, respectively). Finally, participants evaluate surveillance AI lowest on both social (M_S = 3.76, SD = 1.15) and personal (M_S = 3.59, SD = 1.06) benefits.

To summarize the main insights of Study 1a, in Fig. 4 we plot the perceived benefits of AI against costs for the four categories of AI applications. All pairwise contrasts are significant for both benefits ($F(3,13580) = 910.56$, $p < .001$) and costs ($F(3,13580) = 722.83$; $p < .001$). In line with P1a, in commercial-like AI, benefits are valued over the perceived costs. In contrast, in surveillance AI, perceived costs surpass perceived benefits (P2a). Perceived benefits for social personal and impersonal AI

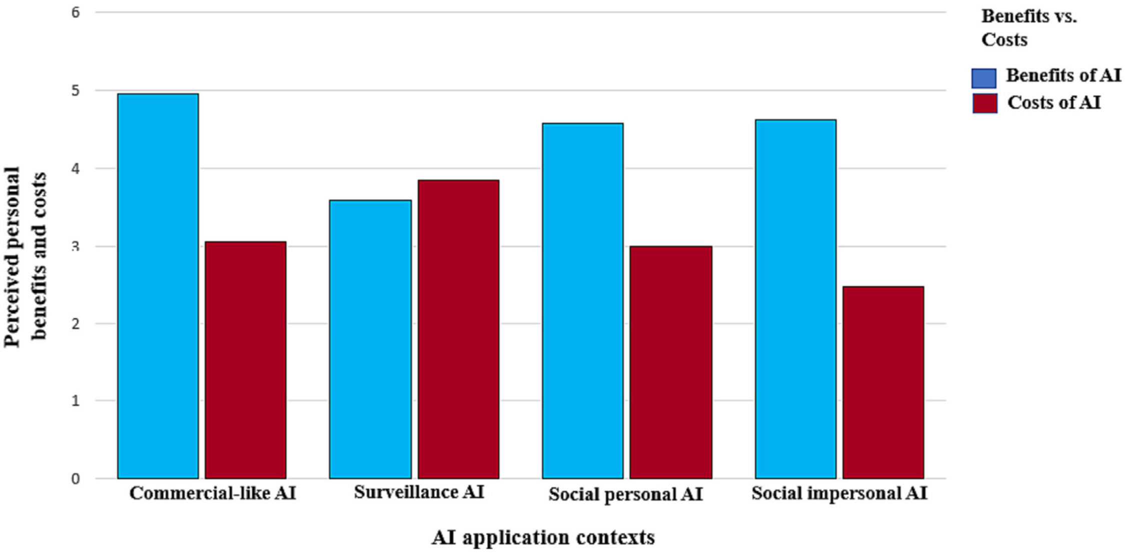

Fig. 4. Perceived benefits and costs of AI across four categories. Notes: The figure illustrates aggregated evaluations of 4,523 respondents of the perceived benefits (personalization, efficiency gains, ease of use, usefulness, helpfulness, ability to improve quality of life) and perceived costs (privacy harms, fears of being hurt, scares, fears of job loss) of AI, on agreement scales (1 = "completely disagree," 7 = "completely agree"). The evaluations of the 21 specific AI contexts are grouped into four categories.

are lower than in commercial-like AI (P3a), and their perceived costs are smaller too, particularly for social impersonal AI (P4b).

4.3. Study 1b: Drivers of adoption/support of AI implementation across contexts

Using the responses to the surveys in Study 1a, we explore the individual-level effects of benefits and costs on the likelihood of adopting an AI application by specifying a panel regression model, in which the 21 AI application contexts (Appendix A) are nested within the individual participants who evaluated them. The main dependent variable is the composite score of the three AI adoption and support preference items used in Study 1a. We also create composite scores for items that indicate personal benefits, societal benefits, and perceived costs (Supplementary Web Appendix, Table W2). The following two-way fixed effect model indicates the support preference expressed by individual i for an AI application context j:

$$\mathrm{AISupport}_{ij} = \alpha_i + \theta_j + \beta_1 \mathrm{BenP}_{ij} + \beta_2 \mathrm{SocBen}_{ij} + \beta_3 \mathrm{Cost}_{ij} + \gamma \mathrm{Cat}_j + Z_i \delta + \mathrm{Cat}_j \tau_j * \left(\mathrm{BenP}_{ij} + \mathrm{SocBen}_{ij} + \mathrm{Cost}_{ij}\right) + \varepsilon_{ij} \quad (1)$$

where α_i captures effects specific to the individual; θ_j captures effects specific to each of the 21 AI contexts; β_1 refers to the effects of perceived personal benefits (e.g., effectiveness, personalization, usefulness); β_2 pertains to the impact of societal benefits (e.g., improving society, reducing social inequalities); β_3 reflects the influence of perceived costs (e.g., privacy, fears, job loss); Cat_j is a categorical variable that indicates the conceptual category to which a technology belongs (surveillance, social personal, or social impersonal), relative to the baseline of commercial-like AI; and Z_i is a vector of individual-level characteristics, such as perceived knowledge of AI, trust in AI, trust in government, level of perceived control, age, gender (female or other), political orientation (conservative or other), residence (EU & UK or other), income (lower than median), and fear of COVID. Finally, the vector of coefficients τ_j represents interaction effects between the type of category and perceived benefits and costs, and the random disturbance term ε_{ij} is assumed normal, with a zero mean. We estimate the effects using a feasible generalized least squares method (Croissant & Millo, 2008). Lagrange multiplier tests of two-way (individual and time) effects, based on the results of the pooling model (Gourieroux et al., 1982), reject the null hypothesis and affirm the appropriateness of the two-way fixed effects model (χ^2 = 347.76, p =.000). A Hausman test of fixed versus random effects model specifications (technology and individual effects) indicates a random effects model is possible (χ^2 = 23.085, df = 25, p =.5726). Comparing the two-way fixed versus random (technology) effects models, the same significance and direction of the estimates emerge, so we opt to use the two-way fixed effect model and account for potential unobserved individual and technology differences using robust standard errors. The resulting R-square value of the model is 0.65 (Adj. R^2 = 0.47).

The results in Table 1 reflect the effects of benefit and cost evaluations on adoption support for AI. The baseline category is commercial-like AI, against which we compare the other three categories. Both personal and societal perceived benefits have positive impacts on support, but personal benefits exhibit stronger effects than societal benefits do (0.530 and 0.183, respectively). Perceived costs have strong negative (-0.162) effects on support for commercial-like AI, though weaker than those of personal or social benefits, as postulated in P1b.

Table 1
Results of panel regression models

	Model 1			Model 2		
	Est.	Std. Error	Pr(>|t|)	Est.	Std. Error	Pr(>|t|)
Personal benefits	0.530	0.033	***	0.500	0.027	***
Societal benefits	0.183	0.031	***	0.254	0.025	***
Cost	-0.162	0.022	***			
Choice autonomy	0.025	0.004	***	0.018	0.003	***
Knowledge	0.001	0.008	Ns	0.013	0.005	*
Trust in AI	0.347	0.011	***	0.354	0.010	***
Trust in government	0.066	0.009	***	0.068	0.007	***
Fear of COVID	0.022	0.010	*	0.028	0.007	***
Political orientation (conservative)	-0.096	0.037	**	-0.046	0.025	.
Country of residence (EU & UK)	-0.080	0.048	.	-0.075	0.032	*
Age (>mean)	-0.037	0.028	ns	-0.043	0.018	*
Income (<median)	0.008	0.041	ns	-0.019	0.026	ns
Gender (female)	-0.037	0.028	ns	-0.029	0.019	ns
Personal benefits: Social impersonal AI	-0.219	0.040	***	-0.213	0.032	***
Personal benefits: Social personal AI	-0.158	0.042	***	-0.157	0.034	***
Personal benefits: Surveillance AI	-0.259	0.047	***	-0.260	0.040	***
Societal benefits: Social impersonal AI	0.021	0.040	ns	-0.018	0.032	ns
Societal benefits: Social personal AI	0.074	0.041	.	-0.021	0.033	ns
Societal benefits: Surveillance AI	0.164	0.046	***	0.141	0.038	***
Costs: Social impersonal AI	-0.087	0.025	***			
Costs: Social personal AI	-0.080	0.027	**			
Costs: Surveillance AI	-0.083	0.030	**			
Intercept	[b]			-0.192	0.144	ns
Category: Social personal AI				1.612	0.163	***
Category: Surveillance AI				1.013	0.169	***
Category: Social impersonal AI				0.893	0.178	***
Privacy				-0.036	0.014	*
Fears				-0.071	0.015	***
Job loss				-0.062	0.006	***
Time trend				-0.029	0.012	**
Social impersonal AI: Privacy				-0.074	0.019	***
Social personal AI: Privacy				-0.029	0.018	ns
Surveillance AI: Privacy				-0.014	0.020	ns
Social impersonal AI: Fears				-0.004	0.020	ns
Social personal AI: Fears				-0.031	0.019	ns
Surveillance AI: Fears				-0.055	0.021	**
	Total Sum of Squares: 10,424 Residual Sum of Squares: 3646.1 R-Squared: 0.65024 Adj. R-Squared: 0.47185 F-statistic: 505.677 on 22 and 5984 DF, p-value: < 2.22e-16			Total Sum of Squares: 21,106 Residual Sum of Squares: 5526.7 R-Squared: 0.73814 Adj. R-Squared: 0.73727 X^2: 25391.8 on 30 DF, p-value: < 2.22e-16		

Notes: Panel regressions with evaluations of technologies nested within individuals. The regression indicates the perceived benefits and costs of AI application evaluations, controlling for AI category, type of application, and individual characteristics on willingness to support, as in Equation (1). M1 = two-way fixed effects model (21 AI application θ_j estimates and 4,523 α_i individual effects); M2 = random-effects model with distinction in different types of costs (fears, privacy, job loss)

*** p =.000, **p =.001, *p =.05,.p =.10, ns = not significant.

When we control for personal and AI category–related differences, the interaction effects (thetas in Equation (1) indicate that the perceived impact of increasing *personal benefits* is significantly lower for public AI categories (social impersonal, social personal, and surveillance AI) than for commercial-like AI. A one-unit increase in perceived personal benefits for surveillance AI is only half as strong as the impact of increasing personal benefits for commercial AI (0.530 – 0.259). The effects of personal benefits of social personal AI are weaker than the personal benefits of commercial AI (0.530 – 0.158), in line with P3b.

Societal benefits have strong main effect on support (0.183) for the commercial-like AI. Compared with this lift, the effect of increasing the perceived societal benefits is most significant for surveillance AI; an increase in perceived societal benefits (e.g., improved public safety) increases support for surveillance AI (0.183 + 0.164), even beyond the lift for the commercial-like AI. In line with P2b, support for surveillance AI can be enhanced strongly by perceptions of societal benefits.

Perceived costs have negative main effects on support for AI in commercial-like applications (-0.162), which become even more negative when the perceived costs increase in the other three categories: social impersonal AI (by -0.162 – 0.087), social personal AI (by -0.162 – 0.080), and surveillance AI (by -0.162 – 0.083). For comprehensiveness, we list the effects of the individual control variables in Table 1. The perceived level of personal control over AI (choice autonomy), trust in AI, and trust in government all have positive, significant effects on support for AI (0.025, 0.347, and 0.065, respectively).

The more concerned respondents are about COVID-19, the stronger the effects on their support for AI (0.022). People with conservative political orientations express less support for AI applications (-0.096). Gender, income, age, and location do not exert significant effects.

Finally, to explore fears beyond privacy concerns or job loss, we specify Model 2 in line with Equation (1), but instead of a composite score for costs, we include separate variables for privacy concerns, job loss, and fears (''scares me,'' ''harms me''). To increase the efficiency of this estimation, we use a random individual effects model (Hausman test, χ^2 = 25.591, df = 24, p =.374). Even for the main effect (commercial-like AI), an increase in fears exerts a more detrimental effect on support than do increases in privacy concerns (-0.071 versus -0.036, respectively). Indicating the need to explore these effects separately, we find that the effects of fears are amplified for surveillance AI, such that they significantly reduce support for it, more so than privacy concerns do (the only significant interaction effect is for surveillance AI, -0.071 – 0.055). Compared with commercial AI, increased privacy concerns in social impersonal AI amplify the negative effects of privacy concerns (-0.036 – 0.074). These findings suggest the relevance of P2a; fears, on top of privacy concerns, affect adoption. Moreover, as P4b suggests, perceived privacy concerns and fears are lowest in social impersonal AI contexts. Increased privacy concerns are particularly detrimental to their adoption.

5. Study 2: Benefits and costs across AI solutions and contexts

Study 1 confirms contextual differences in evaluations of benefits and costs of AI applications and shows that these differences affect adoption likelihood for AI implementations. But the survey does not allow us to determine whether the contextual effects are driven by the sector, as represented by the entity that implements the AI (commercial versus public), or by the specific AI application (e.g., chatbot versus air quality monitoring). In Study 2, we use an experimental approach to analyze the same underlying AI applications across public versus commercial implementation contexts. It features a 4 (categories of AI applications: chatbots, surveillance cameras, self-driving vehicles, air quality sensors) $\times$ 2 (sectors: commercial, public) between-subjects design. The study was preregistered on the OSF[1] platform; the experiment was conducted on the Prolific academic platform. After signing consent forms, 800 participants were randomly assigned to one of the experimental conditions. After excluding those who failed attention checks, the sample included 790 respondents (50% women, 2% other; M_{age} = 33.36 years, SD = 12.30). The scenario described an AI application context, which participants evaluated before reporting their demographic information (see the Supplementary Web Appendix, Table W3).

5.1. Experimental design

We selected four AI technologies, representative of each quadrant in our conceptual framework: chatbot (commercial-like AI), self-driven vehicles (social personal AI), air quality monitoring (social impersonal AI), and surveillance cameras (surveillance AI). To manipulate the setting, we told participants that the technology had been implemented by a government or public institution or a commercial company (see Appendix B).

Using the same scales as in Study 1, respondents evaluated perceived personal benefits, societal benefits, costs, and likelihood to support adoption (Supplementary Web Appendix, Table W1). We specified the tensions as main dependent variables on a semantic differential scale, with the prompt, ''To what extent do you feel that this technology: Benefits you–Benefits society/Serves you–Exploits you'' (1–7 slider scale, anchored at the middle of the semantic differential). A manipulation check asked about the extent to which the technology served a commercial purpose, and attention checks asked what type of technology was present in the scenario and who had implemented it (10 respondents failed one or both checks). We used a series of general linear models (with Bonferroni correction) to explore the differences in evaluations across experimental conditions. Participants in the public AI contexts perceived the AI solutions as having less of a commercial purpose (M_P = 4.93, SD = 1.39) than participants in the commercial AI contexts (M_C = 5.51, SD = 1.09; F(1, 789) = 42.68, p <.001). Participants in the commercial AI contexts were more likely to perceive control and high autonomy over the AI application (M_C = 3.51, SD = 1.57) than participants assigned to the public AI contexts (M_P = 3.18, SD = 1.61; F(1, 789) = 8.31, p =.004). Participants indicated the least control over surveillance cameras (M_S = 2.82, SD = 1.58), followed by chatbots (M_C = 3.20, SD = 1.50), self-driving vehicles (M_{SP} = 3.24, SD = 1.48), and air quality sensors (M_{SI} = 4.12, SD = 1.54; F(3, 789) = 25.65, p <.001).

5.2. Results: Impact of commercial vs. public context on tensions

5.2.1. Tensions between personal and societal benefits

As illustrated in Fig. 5, societal benefits overcome personal benefit evaluations for public sector relative to commercial sector applications (M_P = 5.11, SD = 1.52; M_C = 4.45, SD = 1.55; F(1,789) = 42.751, p >.001). Pairwise comparisons reveal significant differences in perceptions of tensions between personal and societal benefits, depending on the (commercial vs. public) sector (F(3, 789) = 15.342, p <.001), in line with our assertion that evaluations of public AI implementations cannot be predicted from customer responses to equivalent commercial AI applications. Regarding the differences among the four

[1] Link to the preregistration: https://osf.io/5pmrz/?view_only=dc6285c58898441e8a3f716c447f9d54.

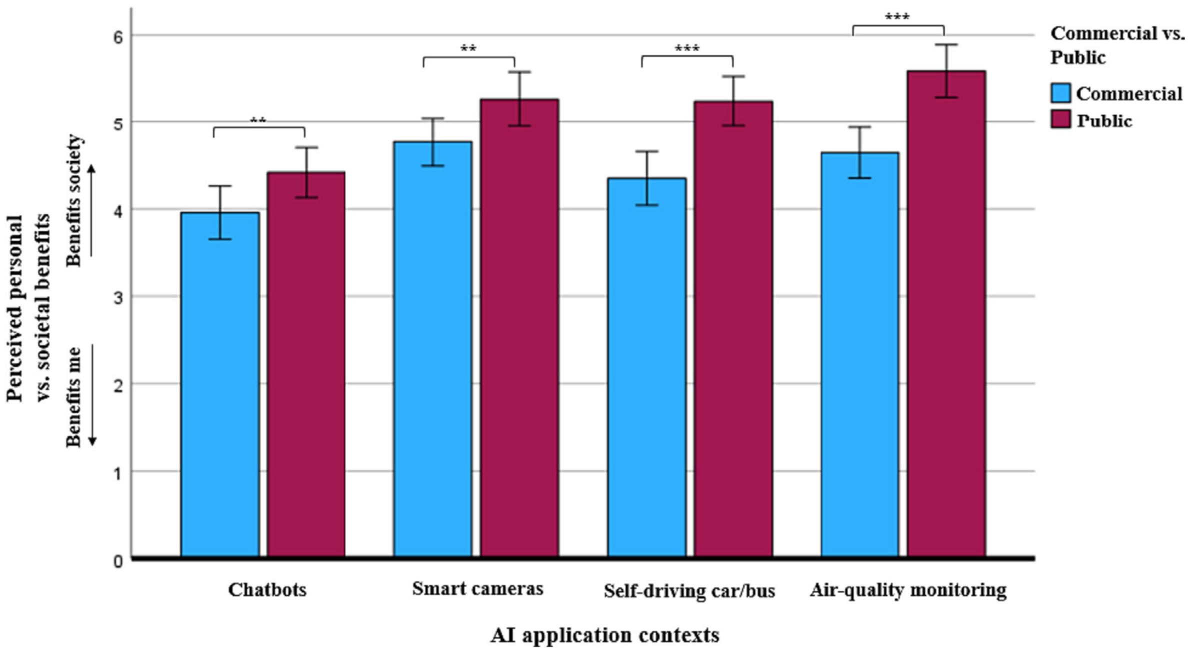

Fig. 5. Tensions of perceived personal versus societal benefits
Notes: On a semantic differential scale, respondents indicated the extent to which they believed the AI implementation context described in the scenario benefitted themselves versus society (1 = "benefits me," 7 = "benefits society"). Bonferroni adjustments for multiple comparisons. ** p <.05; *** p <.001.

categories, we find particularly significant differences in evaluations of the benefits of chatbots; participants perceive their higher personal than social benefits compared with other contexts. Regarding the tensions between personal and societal benefits, the interaction of application categories and sectors is not significant (p =.229).

5.2.2. Tensions between feeling served or exploited

Fig. 6 depicts the differences in tensions between being served versus exploited, depending on the implementation context. These tensions differ significantly only according to the category of AI application ($F(3, 789) = 29.43$, p <.001), not by sector ($F(3,789) = 1.24$, p =.265). The participants feel the most served, rather than exploited, by social impersonal AI (air quality sensors; $M_{SI} = 2.48$, SD = 1.48), followed by social personal AI (self-driving vehicles; $M_{SP} = 2.74$, SD = 1.34), and only then commercial-like AI (chatbots; $M_C = 2.87$, SD = 1.33) and surveillance AI (cameras; $M_S = 3.92$, SD = 1.71). In line with P2a, the feeling of being exploited (cf. served) is significantly higher in surveillance AI, relative to all other contexts, in public and commercial contexts. The significant interaction effect between categories of AI application and sector (p =.036) indicates that participants feel more exploited by surveillance cameras in commercial ($M_C = 4.18$, SD = 1.85) than in public ($M_P = 3.65$, SD = 1.52; p =.022) contexts. As P2b suggests, surveillance AI applications are more acceptable when implemented by public rather than corporate entities, which might reflect people's appreciation for algorithms over human judgments in contexts that threaten the presence of human biases (Logg et al., 2019).

5.2.3. Adoption

We find a main effect of the category of AI application on adoption ($F(3, 789) = 31.478$, p <.000), such that participants are most likely to support air quality systems ($M_{SI} = 5.78$, SD = 1.11), followed by chatbots (M = 4.97, SD = 1.47), surveillance cameras ($M_S = 4.56$, SD = 1.61), and self-driving vehicles ($M_{SP} = 4.52$, SD = 1.59). All pairwise comparisons are statistically significant, except the difference in adoption intentions between surveillance and self-driving vehicles, which may reflect similar fear levels. Within each AI context, support intentions are similar across public and commercial settings, indicating no interaction effects. On a measure of *reactance* to AI ("I would actively oppose an introduction of such AI solution"; 1 = "completely disagree," 7 = "completely agree"), we find low scores overall, such that the mean across all contexts is 2.65 (range 1.78–3.04). No significant differences arise between the commercial and public sector contexts within a category. However, we identify significant differences across categories of applications. Specifically, reactance is least to air quality sensors, but highest and equivalent for surveillance cameras and self-driving vehicles (average across public and commercial contexts: $M_{SI} = 1.93$; $M_S = 2.99$; $M_{SP} = 2.96$; $F(3,789) = 7.66$, p <.001).

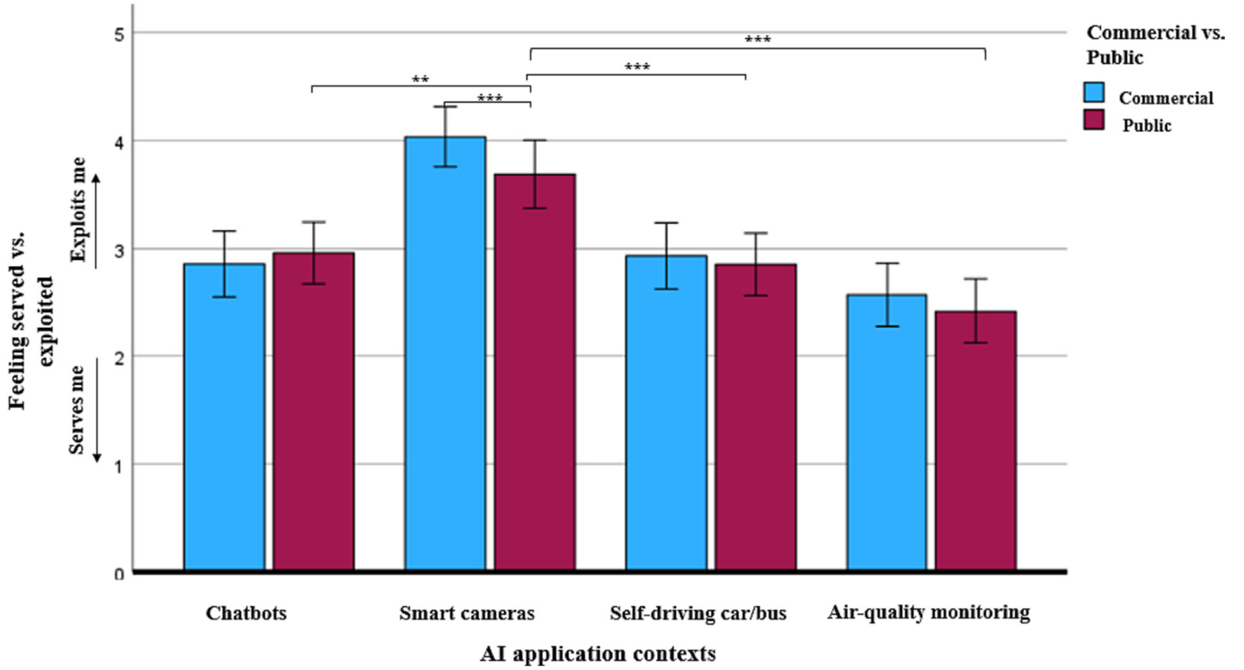

Fig. 6. Tensions of feeling served versus exploited. Notes: On a semantic differential scale, respondents had to indicate the extent to which they believe the AI implementation context described in the scenario serves versus exploits them (1 = "serves me," 7 = "exploits society"). Bonferroni adjustments for multiple comparisons. Only selected significant effects for public AI are displayed in the graph, to reduce complexity. ** p <.05; *** p <.001.

5.3. Mediation analysis

We test the impact of perceived tensions on adoption using parallel mediation with the PROCESS macro (model 4, Hayes, 2018). We run the model with 10,000 bootstrap analyses, using adoption as the main dependent variable, the four categories of AI application as the main independent variable (baseline = commercial-like AI), and the tensions between perceived personal versus societal benefits, and between feeling served versus exploited, as mediators. In line with our expectations, greater societal relative to personal benefits increase the likelihood that respondents support the application (b = 0.06, SE = 0.02, p =.003), whereas a stronger sense of being exploited than served leads to diminished support (b = - 0.50, SE = 0.02, p =.000).

Marked differences also arise in relation to the extent to which AI categories predict adoption through the two mediators. Relative to commercial AI, the other three categories evoke higher perceived societal benefits. An increase in perceived societal benefits in these contexts prompts more support for AI implementations, relative to commercial-like AI (surveillance AI 0.04, BootSE = 0.02, 95% confidence interval [CI] [0.0005, 0.1034]; social personal AI 0.38, BootSE = 0.02, 95% CI [0.0004, 0.0885]; social impersonal AI 0.05, BootSE = 0.02, 95% CI [0.0006, 0.1181]). For the mediation through the feeling of being served versus exploited, we find a significant effect for surveillance and social impersonal AI, but not for social personal AI. People feel more exploited than served in surveillance AI than in the commercial-like AI, which leads to lower support for the AI solution (- 0.49, BootSE = 0.08, 95% CI [- 0.6662, - 0.3311]), in line with P2b. Yet relative to commercial-like AI, people feel less exploited than served in social impersonal AI, which leads to higher support (0.21, BootSE = 0.07, 95% CI [0.0672, 0.3638]), in line with P4b. For social personal AI, the feeling of being served rather than exploited is similar to that for commercial-like AI, such that we find no difference between contexts, as we proposed in P3b. Finally, the direct effect of social personal AI (b = - 0.49, SE = 0.12, p =.00) and social impersonal AI (b = 0.54, SE = 0.12, p =.00) on adoption is significant. The direct effect of surveillance AI on adoption is not (b = 0.03, SE = 0.13, p =.78). Feeling exploited fully mediates this relationship.

6. Study 3: Choice-based conjoint analysis of trade-offs in AI adoption

In Study 3, we employ a choice-based conjoint design to explore the causal effects of the trade-offs people make when they evaluate an AI implementation. Compared with traditional experimental designs, conjoint designs provide two main advantages (Hainmueller et al., 2014). First, we can estimate the trade-offs between multiple treatment components and

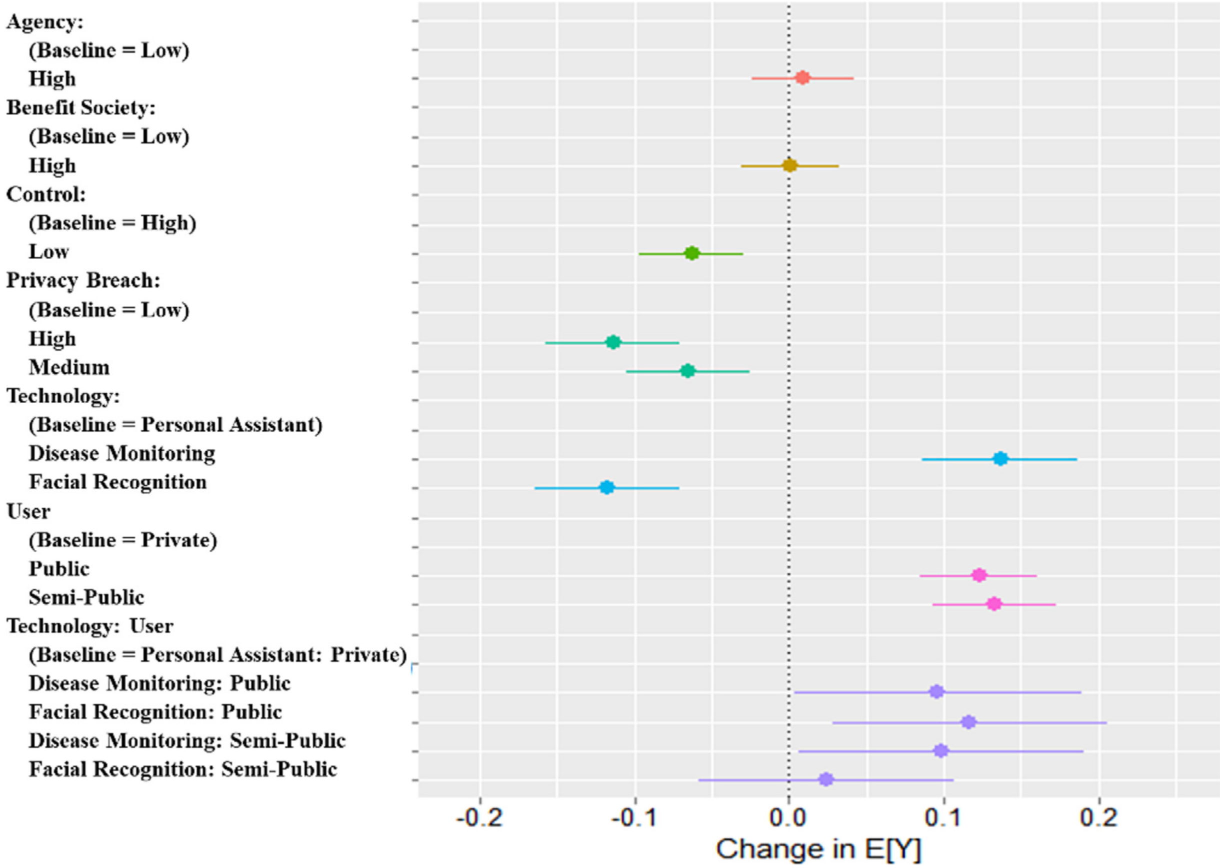

Fig. 7. Choice-based conjoint trade-offs. Notes: Respondents had to "Choose which of these implementation solutions you would support (A, B, None)," randomly repeated five times per respondent. The ACME estimate (colored dot) includes bars representing 95% CIs, which indicate the effect on the expected probability of preferring or choosing the profile when an attribute changes from the baseline level (in brackets) to another level (average over the randomized distribution of all the profiles included in the conjoint). For example, changing the technology from voice personal assistant to disease monitoring increases the probability of choosing that profile option by δ percentage points. Detailed results presented in the Supplementary Web Appendix, Table W5.

how they influence the choice to support a public AI, such that we can determine the relative powers of competing and complementary public policy solutions. Second, respondents are not explicitly asked to evaluate the desirability of an attribute in isolation, so the conjoint experiment alleviates concerns about social desirability, which is particularly relevant for trade-offs that require sacrificing personal benefits and costs for a social good.

6.1. Measures

Three hundred sixty-seven participants from the Prolific platform had to choose repeatedly among different AI solutions (37% women, average age = 25.57 years; see Supplementary Web Appendix, Table W4). Participants tend to perceive commercial-like AI and social personal AI in a similar way, and their tensions are alike, as are their impacts on adoption. Therefore, to reduce complexity, we selected three contexts, representative of the main categories of AI applications (commercial-like, social AI, and surveillance AI): virtual personal assistant, disease spread monitoring, and facial recognition surveillance.[2] All three contexts breach users' privacy to some degree, so respondents must trade off their benefits and costs. Rather than evaluate each attribute separately, participants chose which AI solution (including the type of application and setting) they wanted to see implemented in a public context, or else "None of the available options" (Appendix C). The solution profiles varied on the following attributes, which we chose because they fall under the control of policy makers: the *owner and user* of collected data (private, semi-public [airport], public), level of *AI agency* in automated decision-making (low, high), level of *control over data by citizens* to represent autonomy (low, high), level of *social* versus *private benefit* (low, high), and level

[2] This study was conducted while the COVID-19 pandemic was ongoing, so these technologies were likely to be both familiar and salient to respondents.

of *privacy breach* (face recognition, blurred facial characteristics, full anonymization of face and skin features). To describe the AI solution, we use definitions and images similar to those in Study 1 (Appendix C). As control covariates, we include familiarity with the technology (Logg et al., 2019), trust in government to implement the technologies (Nam, 2019), general trust in government (Nam, 2019), demographic information (employment, gender, country of origin, age, political orientation, income), and concern about COVID-19 (Ahorsu et al., 2020).

6.2. Results

To analyze the marginal effect of each attribute's influence on the probability that a profile (solution) would be chosen, we compute the average marginal component effect (AMCE) of each attribute, averaged over the joint distribution of the remaining attributes (Hainmueller et al., 2014). Thus, the AMCEs can be straightforwardly interpreted as a causal estimate of the expected change in the probability of supporting the introduction of an AI solution, for a given attribute value, compared with the baselines and controlling for all other multidimensional influences on choice. For our evaluations, we use the following baselines: low autonomy, low benefits for society, high control over the data, low privacy breach, private user, and personal virtual assistant. Fig. 7 shows the AMCEs at 95% CIs for each attribute value, which reveal how much better or worse a randomly selected AI solution (profile) would fare if the user switched from a commercial company to a public institution (user attribute).

The results indicate that the choice to support the AI application increases by 0.13 (SE = 0.025) for the disease surveillance solution, relative to the voice virtual assistant. But changing the AI application from the virtual assistant to facial recognition software reduces the probability of choosing the solution profile by 11 percentage points (0.11, SE = 0.023). People are substantially more likely to support the technology if the user switches to a public (0.12, SE = 0.019) or semi-public (0.13, SE = 0.024) institution, relative to a private company. Moreover, the probability of supporting the solution among consumers with low control over the data is 6 percentage points lower (0.06, SE = 0.016) than for consumers with high control. Changing the perceived privacy breach level, from low (complete anonymization of features and personal characteristics) to medium (blurring facial features), reduces the expected likelihood of choice by 6.5 percentage points (SE = 0.020); high levels of privacy breach (face recognition) reduce the likelihood of choice by 11 percentage points (SE = 0.020). Neither the extent to which the technology might benefit society nor the autonomous decision-making levels significantly affects the probability of choosing a particular public AI solution.

We also calculate average component interaction effects from the interaction effects between the AI application and the type of user. They reveal that the choice to support a solution depends on who owns the data collected by the technology. This choice is 9.6 percentage points higher (SE = 0.047) if the application is disease monitoring and the data are owned by public entity, compared with a voice assistant employed by a public company; 11.7 percentage points (SE = 0.045) higher for facial technology employed by a public entity; and 9.8 percentage points (SE = 0.047) higher for disease monitoring by a semi-public entity.

7. Discussion and policy implications

Not only does AI affect personal consumption patterns, but it also defines how people interact with governments (Desouza et al., 2020), the information they receive about political issues and candidates (Isaak & Hanna, 2018), the type of healthcare professionals they encounter (Mende et al., 2019), and the society in which they live (Zuboff, 2019). However, empirical studies into the trade-offs and tensions across diverse contexts for AI implementation are scarce (Puntoni et al., 2021; Zuiderwijk et al., 2021). As we establish, support for and adoption of AI are driven by citizens' experiences of AI and the affective, symbolic, and functional elements they trade off when evaluating an AI solution (Grewal et al., 2021; Mick & Fournier, 1998). Specifically, evaluations of the costs and benefits of AI, and the resulting tensions between feeling served (personal and societal benefits) versus feeling exploited (perceived costs to the individual and society), differ across contexts, as are represented by an AI application implemented in a specific setting for a particular purpose. In Table 2, we summarize the implications of these findings for public policy makers and AI implementation managers as they deploy new AI solutions and devise AI regulations.

In addition, our findings offer implications for marketing and public policy researchers. When confronted with complex sociopolitical issues, many citizens rely on the government to provide a solution, due to their perceived lack of knowledge or control (Shepherd & Kay, 2012). Therefore, policy makers should establish context-dependent communications of benefits and costs, offer transparency, and establish trust to reduce uncertainty (Venkatesh et al., 2016; Walker 2016). They need to move beyond polarized debates or functional silos that assess benefits and costs in isolation (e.g., between privacy activists and AI developers) to acknowledge and understand the citizen-centric tensions that can affect social welfare (Twizeyimana & Andersson, 2019; Zuzul, 2019).

Notably, weak appreciation of societal relative to personal benefits and greater threats to privacy and fears are powerful obstacles to the adoption of public AI. Many public AI applications emphasize benefits to society, which may be ineffective; we find that personal benefits and costs are the main drivers of AI adoption AI. In commercial applications, users tend to emphasize the personal benefits of efficiency, personalization, and ease of use over less salient personal costs (e.g., privacy)

Table 2
Policy implications of public versus commercial AI and deployment issues.

	Public AI Applications	*Commercial AI Applications*	*Deployment Issues*
Personal benefits	• Familiarity with commercial-like applications drives higher perceived usefulness and appreciation. • Context-dependent appreciation based on perceived personal costs (feeling served only if personal costs are low).	• High perceived personal benefits drive efficiency and usefulness perceptions. • Personal benefits form the feeling of being served.	In communication, personal benefits should be emphasized in solutions directed toward the person.
Societal benefits	• Societal benefits are undervalued if personal costs arise (e.g., security versus privacy). • Societal benefits are strongest in settings directed toward infrastructure.	• Societal benefits are less salient in evaluations of AI applications.	Societal benefits have lower impact on choice than personal benefits. In contexts with high personal costs, increasing perceived societal benefits increases support.
Costs emphasis	• Fears in social contexts go beyond privacy concerns. • Personal costs drive feeling exploited. • Cost perceptions are strongly affected by reduced senses of control and autonomy.	• Costs are less salient and underestimated in commercial-like AI. • Fears beyond privacy are less salient. • Lower cost perceptions are driven by higher perceived control and autonomy.	Leverage data collection transparency: government control over data is supported more than corporate control. Privacy-protecting solutions significantly increase support and adoption, by lowering personal costs. Increase in privacy concerns is detrimental for social impersonal AI.
Sector (public vs commercial)	• Public AI implementation should not assume evaluations of benefits equivalent to those for commercial AI.	• People feel more exploited by privacy-breaching applications in commercial than public contexts.	Even for familiar commercial applications, public AI must carefully evaluate perceived benefits versus costs.
Tensions	In contexts with high personal benefits or low personal costs (infrastructure), perceived benefits overcome costs and drive support for adoption. In contexts with high personal costs, societal benefits of feeling served or protected are undervalued relative to the feeling of being exploited.	Personal benefits of feeling served overcome the costs of feeling exploited. Regulation is needed for less salient contexts of feeling exploited in commercial settings.	Social impersonal solutions evoke low tensions; societal benefits should be emphasized. Tensions in evaluations of benefits reflect the sector (public vs. commercial). Surveillance AI is subject to fears, so regulatory protections of data should be emphasized, relative to various fears, not just privacy.

(Acquisti et al., 2020). Although we find a generally positive effect of societal benefits for public AI, it is weaker than that of personal benefits in terms of convincing people to support public AI applications when personal costs are salient. Conversely, the perceived tensions are lowest (and acceptance is high) when AI implementation bears distant, low perceived personal costs (e.g., social impersonal AI; disaster monitoring, air quality monitoring). For example, traffic monitoring solutions may be able to identify people, just as CCTV cameras can in public spaces. But these personal costs seem less salient to citizens' evaluations of public AI directed at infrastructure (rather than humans), leading to significantly higher support for traffic monitoring than for surveillance AI.

In contexts in which technologies appear intrusive on civilian liberties and privacy, costs rather than benefits drive evaluations. In those cases, increasing perceptions of societal benefits (and/or reducing fears) can encourage citizens' support. However, prior research tends to combine diverse concepts under a privacy banner, which makes it hard to distinguish the true impact of privacy concerns from that of other fears that arise in public contexts (e.g., fear of surveillance, loss of obscurity, social harms). In particular, we advocate for AI and privacy research to take a multidisciplinary approach to explore diverse types of fear, which can have important implications for AI support.

Perceived autonomy and control may play significant roles too (Botti et al, 2023). People's willingness to share personal data with firms depends on the context and increases when customers perceive a better fit between the type of data collected and the purpose (e.g., core business of the firm) (Ackermann et al., 2022). However, the perceived benefits of increased access to personal data for increasing efficiency appear to have mixed effects in public contexts—increasing acceptance of efforts to monitor terrorism suspects and domestic leaders but not monitoring fellow citizens or the self (Nam, 2019). We show that increasing perceived societal benefits has the strongest positive impact on support for surveillance AI technologies, particularly if the AI applications are the responsibility of public entities rather than commercial institutions. We also find initial support for governments' attempts to improve data transparency and provide data protection through anonymization of data collection and higher transparency of data ownership and use, which increase support for public AI.

This increase in societal benefits seemingly should stem from the feeling that AI increases perceived social welfare. With a large field experiment, Athey et al. (2017) find that perceived government surveillance can lead consumers to be more protective before linking personal identity information to their digital cryptocurrency accounts. However, their privacy protective behaviors are malleable in the presence of irrelevant, reassuring information about privacy protection through encryption. The mere presence of irrelevant encryption randomization information (with no direct impact on privacy protection) renders consumers less likely to try to escape surveillance. We hope to encourage more research into the contextual dependence of AI tensions and societal welfare, in particular to understand the trade-offs in choices that may facilitate or impair social welfare (Botti et al., 2023). For example, it is not clear how emphasizing different threats versus benefits might affect evaluations of public AI and choice freedom. In the commercial context of mobile payment systems, Story and colleagues (2020) find that increasing people's awareness of threats to security enhances their likelihood of adopting protection mechanisms, particularly if they are prompted to formulate an implementation plan. But we know little about the potential countereffects of such strategies in public AI implementation contexts, where increased awareness of a threat may backfire. For example, the severity of the threat might be over- or underestimated, due to people's inherent cognitive biases that underestimate the possibility of threats to their security (Acquisti et al., 2020). Thus, we need more research into whether a new paradigm is emerging, in terms of how citizens view the role of government and regulatory power over data transparency and ownership. Our findings may indicate a "silent" shift to post-materialist values of freedom, societal well-being, and care for environment and community (Inglehart, 1981).

More research also is needed to explore the potential spillover effects of public AI practices and implementations on commercial AI. Can we find the Brussels effect from public AI consideration on commercial AI, as well as other public AI, on a global level? The EU AI Act incentivizes changes to products offered in non-EU countries, particularly by large U.S. tech firms. It arguably could influence global regulations, by offering an influential operationalization of what it means to develop and deploy trustworthy, human-centered AI (Siegmann & Anderljung, 2022).

Finally, with this exploratory research, we focus on average effects across individuals, but further research could explore individual differences. For example, personal characteristics, including perceived choice autonomy, trust in AI, and trust in government, enhance support for AI implementation in our study; conservative political orientations and COVID-19 fears lower it. Europeans seem marginally less likely to support AI than people from other regions, but we do not find evidence of gender- or income-based differences. Research into such individual- and country-specific differences could demonstrate how they moderate evaluations of benefits and costs. Continued research might explore the tensions that arise in relation to other types of fears too. Furthermore, more evidence is needed regarding the effects of anonymization and how they differ across groups and contexts. Different social groups may have distinct fears of being exploited or discriminated against (Wirtz et al., 2020). Although we provide initial evidence of causal effects of different tensions on support for AI, we do not explore additional causal mechanisms in these contexts. More empirical evidence could reveal causal mechanisms that enhance or diminish tensions for welfare. We thus hope this research encourages further investigations into the welfare effects of implementing public and commercial AI solutions.

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Data availability

Data will be made available on request.

Declaration of Competing Interest

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

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Appendix A. Study 1 stimuli and classification in the conceptual category across 21 technologies

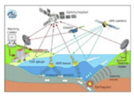
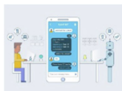
Technology	Description	Image	Adoption/ Support*	Conceptual Category
Local community app	Apps to report on issues in a neighborhood (e.g., abandoned cars, illegal waste dumping, broken public utilities).		5.34	Social personal AI
Smart surveillance	Intelligent monitoring to detect real-time needs for police intervention based on visual feeds including facial recognition, smart closed-circuit TVs, and license plate recognition. These systems are primarily used to prevent crime and help citizens in real-time.		3.31	Surveillance AI
Anonymized surveillance	Intelligent monitoring to detect real-time needs for police intervention based on visual feeds including behavioral traits, body temperature, and posture. The system does not allow to recognize individuals based on face, the color of the skin, or other personally identifiable information.		3.47	Surveillance AI
Digital public administration services	Services offered using technologies to help and engage citizens in society, politics, and government (e.g., online processing of identification documents and e-government services).		5.11	Commercial-like AI
Body-worn cameras	Wearable audio, video, or photographic recording systems, are typically used by police officers to record interactions with citizens, incidents, and police operations.		4.78	Surveillance AI
Remote patient monitoring and check-ups	It involves the interaction between patient and physician through technology. It can include the collection and transmission of patient data for analysis and intervention by a healthcare provider in another location (for example, monitoring vitals or blood glucose readings), medication adherence technologies that assist patients in taking medications, or audio-visual visits.		4.94	Social personal AI
Air quality monitoring	Sensors to detect and monitor the presence of air pollution (outdoor, indoor, or both), temperature, and sounds in real-time. The system uses spatially dispersed and dedicated sensors for monitoring and recording the physical conditions of the environment and organizing the collected data at a central location.		5.66	Social impersonal AI
Infectious disease monitoring	Data collection, analysis, and response to prevent the spread of infectious and epidemic diseases. The surveillance is often used to target consumers with vaccine campaigns (for example, for HIV / AIDS) or advertisements to increase awareness about different diseases and monitor sanitary conditions.		4.81	Social personal AI

Appendix A (*continued*)

Technology	Description	Image	Adoption/ Support*	Conceptual Category
Self-driving busses	Vehicles outfitted with sensors and software to operate themselves; full self-driving capability is achieved when human intervention is not expected to take control at any point.		4.75	Social personal AI
Smart traffic lights	Improvement of overall traffic flow through dynamic optimization of traffic lights and speed limits to reduce congestion and direct traffic flow. Includes traffic light pre-emption technology, which gives priority to emergency vehicles, public buses, or both.		5.39	Social impersonal AI
Wearable devices	Devices that collect data on lifestyle and activity metrics and inform the wearer; may promote exercise or other aspects of a healthy lifestyle.		4.90	Commercial-like AI
Robots in healthcare	Robotic nurses are robots that help patients physically move around or perform simple tasks like taking vital signs or delivering medicine. Robotic-assisted surgeries are surgery performed with the help of clinical robotic systems. The most widely used clinical robotic surgical system includes a camera arm and mechanical arms with surgical instruments attached to them. The surgeon controls the arms while seated at a computer console near the operating table.		4.53	Social personal AI
Police robot	Robots are used for providing police service to citizens and real-time interventions.		3.30	Surveillance AI
Mobility as a service	Shift away from personally owned modes of transportation towards mobility provided as a service that combines transportation services from the public (i.e., busses and subway) and private (i.e., Uber, bike sharing) providers. Through an app, the citizens can plan their trip and receive real-time information about the price, time, and availability of transportation options across many modes of transport, which users can pay for with a single account.		5.25	Social personal AI
Smart home assistant	Devices that allow you to control a range of connected devices in the house from the smartphone.		4.92	Commercial-like AI

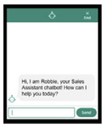
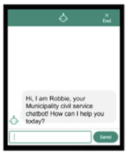
(*continued on next page*)

Appendix A (*continued*)

Technology	Description	Image	Adoption/ Support*	Conceptual Category
Building automation system	A system that optimizes energy and water use in commercial and public buildings by leveraging sensors and analytics. It allows automatic centralized control of a building's heating, ventilation and air conditioning, lighting, and other systems. The core functionality keeps the building climate within a specified range, provides light to rooms based on an occupancy schedule (in the absence of overt switches to the contrary), monitors performance and device failures in all systems, and provides malfunction alarms to building maintenance staff. It should reduce building energy and maintenance costs compared to non-controlled buildings.		5.47	Social impersonal AI
Waste management	Technologies such as RFID tags, GPS, and integrated software packages enable better quality data to be collected without the use of estimation or manual data entry for managing waste. The system uses sensors in waste bins that can identify the level of garbage and automatically inform the central unit that the bin is full. It can also include Digitally enabled pay-as-you-throw systems; it includes feedback (via mobile app, email, text, and so forth) delivered to users to increase awareness (e.g., recycling) and reduce waste.		5.22	Social impersonal AI
Disaster monitoring	Technology is designed to predict and mitigate the effects of natural disasters such as hurricanes, earthquakes, floods, and wildfires.		5.78	Social impersonal AI
Customer service chatbot	A bot that uses artificial intelligence and machine learning to answer basic customer questions via a live chat messenger.		4.43	Commercial-like AI
Drones (delivery drones)	An autonomous vehicle, often an unmanned aerial vehicle (UAV), is used to transport packages, food, or other goods via air.		4.69	Social impersonal AI
Water management	Use of internet-enabled tools (like sensors) to monitor water collection, usage, and drainage with alerts delivered to the public via channels such as mobile apps, email, text, or websites. The sensors can detect the levels of reservoirs and groundwater supply, blockages in pipes, risk of flooding, etc. Areas at risk of flooding can be predicted using flood mapping, historical flood data, and real-time weather information.		5.49	Social impersonal AI

*Willingness to adopt or support AI adoption per context (Likert scale, 1 = "completely disagree," 7 = "completely agree"). Grand mean across all contexts is 4.88 (SD = 0.71).

Appendix B. Scenarios in Study 2

	Chatbot	Cameras	Self-Driving Vehicles	Air Quality Sensors
Commercial	A chatbot is a computer program that uses artificial intelligence (AI) and natural language processing (NLP) to understand customer questions and respond to them in a manner similar to human conversation. Many companies are nowadays using chatbots on their websites to enable customers to search for information and get instant feedback on their queries. 	Smart cameras are vision systems used for video surveillance with built-in image sensors that use artificial intelligence (AI) to identify objects or people in the monitored area. Many companies are nowadays installing smart cameras to monitor customers' behavior inside their stores. 	Self-driving cars are vehicles outfitted with sensors and artificial intelligence (AI) systems that enable such cars to operate themselves (without human assistance). Many companies are nowadays investing in self-driving technologies for future customers' mobility. 	Real-time air quality sensors monitor the quality of the air and detect the presence of air pollution, temperature, and noise in real-time. Many companies are nowadays installing such sensors in their stores to monitor the air quality and noise levels. 
Public	A chatbot is a computer program that uses artificial intelligence (AI) and natural language processing (NLP) to understand citizens' questions and respond to them in a manner similar to human conversation. Many governmental and public institutions are nowadays using chatbots on their websites to enable citizens to search for information and get instant feedback on their queries. 	Smart cameras are vision systems used for video surveillance with built-in image sensors that use artificial intelligence (AI) to identify objects or people in the monitored area.Many cities are nowadays installing smart cameras to monitor citizens' behavior in public spaces such as squares and public areas (e.g., stations) . 	Self-driving buses are vehicles outfitted with sensors and artificial intelligence (AI) systems that enable such cars to operate themselves (without human assistance). Many cities are nowadays investing in self-driving technologies for future citizens' mobility. 	Real-time air quality sensors monitor the quality of the air and detect the presence of air pollution, temperature, and noise in real-time. Many cities are nowadays installing such sensors in public spaces such as parks or squares to monitor the air quality and noise levels. 

Appendix C: Example trade-off in Study 3

(1/5) Please read the description of the technologies carefully. If you had to choose which technology to implement in your city, which one would you choose?

	Option 1	Option 2	None
Type of Technology	 Virtual Personal Assistant - technology (i.e., Alexa, Siri) capable of performing tasks or services for an individual based on commands or questions	 Virtual Personal Assistant - technology (i.e., Alexa, Siri) capable of performing tasks or services for an individual based on commands or questions	None of these options
Who is using your data	Private companies (i.e., Facebook or Apple)	Private companies (i.e., Facebook or Apple)	
Users' control (i.e., the degree to which users have control over the collection and use of personal information)	Low	High	
Autonomy of the technology (i.e., the extent to which the technology operates without human control or intervention)	Low	Low	
The extent to which the main benefits of technology are oriented towards society or an individual	High benefits for society in general and limited benefits for an individual (e.g improved transparency of public decision-making in local communities)	High benefits for individuals and limited benefits to the sociaty as whole (e.g. e-government online documents service)	
Breach of user's privacy	Low (i.e., anonymization: all the personally identifiable information (i.e., face features, voice, skin color, car license plate) are anonymized/blurred)	High (i.e., no anonimyzation: the data collected by the technology are personally identifiable)	

Note: Details about the scales and items used in the studies can be found in the Supplementary Web Appendix.

Appendix D. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijresmar.2023.08.010.

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