

AI Eyes on the Road: Cross-Cultural Perspectives on Traffic Surveillance

ZIMING WANG*, Chalmers University of Technology, Sweden and Stanford University, USA

SHIWEI YANG*, Ghent University, Belgium

REBECCA CURRANO, Stanford University, USA

MORTEN FJELD, Chalmers University of Technology, Sweden and University of Bergen, Norway

DAVID SIRKIN, Stanford University, USA



Fig. 1. AI-enhanced traffic surveillance systems: (a) AI analyzes traffic conditions and recognizes patterns of vehicles and pedestrians (Image courtesy: Travis Buckner); (b) A roadside screen displays jaywalkers, identified using AI, to deter violations (Image courtesy: Gilles Sabri ).

AI-powered road surveillance systems are increasingly proposed to monitor infractions such as speeding, phone use, and jaywalking. While these systems promise to enhance safety by discouraging dangerous behaviors, they also raise concerns about privacy, fairness, and potential misuse of personal data. Yet empirical research on how people perceive AI-enhanced monitoring of public spaces remains limited. We conducted an online survey ($N = 720$) using a 3×3 factorial design to examine perceptions of three road surveillance modes—conventional, AI-enhanced, and AI-enhanced with public shaming—across China, Europe, and the United States. We measured perceived capability, risk, transparency, and acceptance. Results show that conventional surveillance was most preferred, while public shaming was least preferred across all regions. Chinese respondents, however, expressed significantly higher acceptance of AI-enhanced modes than Europeans or Americans. Our

*Both authors contributed equally to this research, and their names are listed in alphabetical order.

Authors' Contact Information: [Ziming Wang](#), Chalmers University of Technology, Gothenburg, Sweden and Stanford University, Stanford, California, USA, ziming@chalmers.se, zmzg@stanford.edu; [Shiwei Yang](#), Ghent University, Ghent, Belgium, shiwei.yang@ugent.be; [Rebecca Currano](#), Stanford University, Stanford, California, USA, bcurrano@stanford.edu; [Morten Fjeld](#), Chalmers University of Technology, Gothenburg, Sweden and University of Bergen, Bergen, Norway, fjeld@chalmers.se; [David Sirkin](#), Stanford University, Stanford, California, USA, sirkin@stanford.edu.

findings highlight the need to account for context, culture, and social norms when considering AI-enhanced monitoring, as these shape trust, comfort, and overall acceptance.

CCS Concepts: • **Human-centered computing** → **Empirical studies in HCI**.

Additional Key Words and Phrases: Traffic cameras, artificial intelligence, cultural influence, technology acceptance, surveillance

1 Introduction

Vision has long been a cornerstone of intelligence, both in nature and in technology [11]. In biological evolution, eyes have enabled survival, navigation, and learning. In computing, cameras function as the “eyes” of machines, capturing raw data that computer vision algorithms transform into perception and interpretation. With the rise of artificial intelligence (AI), these “AI eyes” are increasingly deployed on roads worldwide to monitor traffic, enforce regulations, and optimize urban mobility [48, 86]. Proponents argue that AI-enhanced surveillance can reduce accidents, deter crime, and streamline traffic flow. Yet these promises often come with trade-offs: a loss of privacy, the emergence of the “transparent citizen” [65], and unequal access to digital infrastructures. As AI systems become embedded in everyday life, it is urgent to understand how people perceive and negotiate their presence.

Governance debates underscore this urgency. The European Union’s General Data Protection Regulation (GDPR) [74] has set global precedents for data privacy, and its newly implemented AI Act is poised to extend such influence to algorithmic governance [1, 26]. Policymakers and experts anticipate ripple effects in the United States and China, shaping not only technical standards but also cultural expectations of surveillance [26]. Against this backdrop, traffic surveillance serves as a particularly vivid site for examining public attitudes: it is ubiquitous, consequential for safety, and difficult to opt out of. Unlike consumer technologies, road surveillance systems are woven into the fabric of public life, making their social legitimacy contingent on how citizens experience and evaluate them.

This tension is not abstract. Some countries have experimented with “public shaming” strategies, where surveillance footage of drivers or pedestrians is broadcast to deter misbehavior [17]. China has gone further by pairing facial recognition with large public displays to expose jaywalkers [30], see Figure 1(b). Such practices not only amplify privacy concerns but also reveal profound cultural differences in how AI surveillance is understood. While citizens in Europe and the U.S. often emphasize autonomy and control, Chinese respondents have been found to view AI less as a system to constrain and more as one to connect with, even valuing its capacity to influence behavior [27]. These differences highlight the need for a cross-cultural perspective: the meaning of “AI eyes on the road” cannot be assumed to be universal.

In this paper, we investigate how people in China, Europe, and the USA perceive different forms/modes of traffic surveillance. Our contributions are threefold: (i) we foreground the importance of cross-cultural analysis in debates on AI-enhanced surveillance; (ii) we present findings from an online survey comparing three modes of surveillance—conventional, AI-enhanced, and AI-enhanced with public shaming; and (iii) we propose design recommendations for AI-powered traffic systems that are sensitive to cultural contexts. Together, these contributions advance ongoing conversations about the governance and design of AI, offering insights into how societies might balance safety, privacy, and dignity in the age of algorithmic vision.

2 Background and Related Work

In this section, we lay the foundation for our study by examining gaps in research on surveillance technology, human–AI interaction, and cultural influences.

2.1 Surveillance Technology in HCI

Urbanization and the rise of smart cities have brought surveillance technologies into sharper focus. Designed to enhance citizen well-being [4], smart cities rely on interconnected infrastructures powered by the Internet of Things (IoT) and AI [64, 69]. This interconnectivity has enabled what has been described as a “new smart video surveillance paradigm” [64], where cameras no longer operate as passive recorders but as intelligent systems that interpret and act upon what they see. On the one hand, such systems promise tangible societal benefits: studies demonstrate that surveillance cameras can reduce traffic accidents, deter crime, and support emergency responses [3, 8]. On the other hand, these gains are tempered by challenges, including heightened risks to privacy and civil liberties [35].

HCI research has been central to uncovering the human side of this tension. Studies consistently reveal that coupling cameras with AI intensifies people’s concerns about data collection, storage, and misuse, as well as the broader implications of living under constant monitoring (e.g., [31, 47, 60, 79]). Continuous surveillance can shape behavior itself, as individuals adjust their actions in response to being watched. The perception of being watched by cameras elicited negative emotional responses [77, 79]. From a technical perspective, privacy-preserving methods—such as pedestrian tracking [85] or the more recent Video-to-Text Pedestrian Monitoring (VTPM) that compresses visual input into textual reports [2]—offer potential safeguards. Yet even these innovations are ultimately evaluated by how they align with human values and expectations. As scholars argue, the human factors often outweigh purely technical considerations, because surveillance infrastructures reshape community norms and social contracts [40, 57, 62].

Empirical studies across contexts highlight how perceptions of surveillance are far from uniform. In Detroit, residents adopted a pragmatic “better than nothing” stance, accepting surveillance as a compromise despite misgivings [51]. In Europe, attitudes varied by gender and situational context, with participants rating video systems as “fairly useful” while still acknowledging privacy risks [29]. Messick [55] found that women are significantly more likely than men to accept public surveillance, highlighting the gendered nature of the privacy–security trade-off and the need for female representation in related policymaking. In retail environments, consumer attitudes varied based on the transparency and perceived benefits of surveillance technologies, with voluntary and transparent systems receiving more favorable evaluations [15]. In Vietnam, educational stakeholders evaluated surveillance through a pragmatic lens as well, recognizing its limitations in preventing school violence but also its potential effectiveness in deterrence [73]. Taken together, these findings underscore that acceptance depends on latent factors such as context, transparency, and cultural norms.

To systematize such insights, Krempel and Beyerer [41] proposed the *Technology Acceptance Model for Video Surveillance* (TAM-VS), which emphasizes three interrelated determinants of acceptance: perceived usefulness, perceived risk, and system transparency. These factors provide a structured lens for assessing how people interact with surveillance systems and how such technologies might reshape daily life. In this paper, we argue that TAM-VS is especially relevant for understanding road traffic surveillance. By extending this framework across cultural contexts, we can better illuminate how AI-driven surveillance on roads is negotiated, contested, or normalized in different societies.

2.2 Human-AI Interaction in Daily Lives

Human-Centered AI extends beyond designing systems for individual use—it envisions AI as a technology that should benefit communities and societies as a whole. Human-AI Interaction (HAI) has thus emerged as one of the most transformative developments in recent decades, as AI systems increasingly embed themselves into the infrastructures of daily life. Research has documented their applications in public services such as healthcare [38, 71], transportation [5], welfare [16], and public administration [6, 39]. As Iglar et al. [36] emphasize, this rapid growth of interactive AI calls for tighter integration between HCI and allied disciplines such as human

factors engineering. From generative chatbots [25] and recommender systems [54] to autonomous vehicles [61] and advanced medical diagnostics [70], AI technologies are not only ubiquitous but also increasingly influential in shaping social and organizational life.

This ubiquity brings both opportunities and risks. On one hand, AI provides tangible support in work, mobility, and play, offering new efficiencies and conveniences. On the other, it raises critical concerns about privacy, ethics, and human control [72]. Scholars argue that understanding the psychological and social dimensions of HAI is key to successful implementation [7, 44]. How individuals perceive, interpret, and emotionally respond to AI directly influences adoption, acceptance, and long-term engagement [33]. Trust has emerged as a particularly crucial construct in this space [37]. Yet research reveals that trust in AI is not monolithic but domain-specific: in healthcare, people tend to prefer human over AI decision-making [45], whereas in other contexts AI may be favored for its perceived impartiality and accuracy [28]. Identity disclosure also matters: Nazaretsky et al. [58] found that students favored human-created feedback when the source was explicit, but rated AI-generated feedback more highly when the origin was ambiguous. These nuances highlight that acceptance is not only about technical accuracy but also about how AI is socially framed and culturally contextualized.

Surveillance represents a particularly complex domain for HAI because it sits at the intersection of collective benefit and individual rights [49]. AI-enhanced surveillance can significantly reduce the workload of human operators, enabling consistent monitoring of road activity, quicker detection of traffic violations, and more efficient enforcement of laws. Such effectiveness can translate into reduced accidents, smoother traffic flow, and stronger public safety, echoing adoption patterns seen in domains like AI-powered programming assistants [84] and autonomous driving systems [81]. However, these benefits are coupled with serious concerns. The pervasive nature of surveillance means that individuals' movements and behaviors are constantly recorded, and once augmented by AI, such data becomes subject to powerful forms of analysis, storage, and potential misuse [20, 50]. Public acceptance of these systems depends not only on their effectiveness but also on whether they are perceived as fair, transparent, and proportionate [76].

As such, balancing technological capability with ethical responsibility remains an open challenge. Designing human-AI surveillance systems that promote safety without undermining trust or privacy is still in its early stages. HCI scholarship has a vital role to play in advancing this balance, by uncovering how people interpret, negotiate, and resist AI in their daily lives—and by providing design insights that embed accountability and dignity at the heart of AI-enabled infrastructures.

2.3 Cultural Influence on Attitudes about Privacy, Security, and Surveillance

Cultural influences have been a significant factor of consideration in HCI studies (e.g., [78, 80]). While much of the prior work on surveillance acceptance has examined individual-level factors such as perceived usefulness, risk, and trust, macro-level cultural contexts also shape how people evaluate surveillance technologies. As Yang et al. [82] argue, HCI research must account for the “system–people–policy” nexus, where societal values and governance frameworks interact with technological design. Bareis and Katzenbach [10] analyze how national AI strategies mobilize techno-optimistic narratives and imaginaries that performatively construct AI as inevitable progress. Policies concerning surveillance are not uniform across the globe but instead reflect deeply rooted cultural norms, legal traditions, and political priorities. These differences, in turn, influence public sentiment toward privacy, security, and surveillance.

Europe. European countries have long emphasized privacy as a fundamental right, most notably through the General Data Protection Regulation (GDPR) [74]. The GDPR restricts data retention, requires explicit consent, and has influenced global standards for data protection. Unsurprisingly, European publics often exhibit stronger resistance to surveillance: a 2015 poll found particularly low tolerance in Sweden, Spain, the Netherlands, and Germany [18]. Recent developments, such as the EU's Artificial Intelligence (AI) Act [1], extend these

protections into the realm of algorithmic governance, imposing strict regulations on high-risk applications like facial recognition [24]. Such measures reflect a cultural orientation toward individual rights, legal safeguards, and skepticism of pervasive monitoring.

United States. In the USA, privacy concerns are historically rooted in constitutional protections such as the Fourth Amendment [67]. Surveys show that while Americans often support surveillance measures for national security, they are also wary of government overreach and the erosion of personal freedoms [9, 53]. Public opinion remains divided: some accept surveillance as a necessary compromise, while others fear abuse and loss of autonomy. Unlike Europe, however, the USA lacks comprehensive federal regulations on AI-powered surveillance. Instead, a patchwork of state and municipal laws restrict facial recognition in select contexts, with bans in places like Boston, San Francisco, and Virginia [75]. This regulatory inconsistency mirrors the country’s cultural ambivalence—valuing both personal liberty and strong security measures.

China. In contrast, China represents one of the most expansive implementations of surveillance technologies, deploying more than 200 million cameras in public spaces by 2018 [56]. Surveillance is closely tied to smart city development and public governance, integrating AI to manage traffic, safety, and social order [32]. Strikingly, Chinese citizens generally express higher acceptance of such systems [23], even in controversial practices such as publicly shaming jaywalkers via facial recognition displays. Cultural orientation offers a partial explanation: whereas Europe and the U.S. lean toward individualism, China is often characterized as a collectivist society, where social welfare and harmony are prioritized over individual privacy [14, 43]. In collectivist contexts, compliance with authority and the willingness to trade personal autonomy for collective benefits may contribute to greater tolerance of surveillance.

Taken together, these contrasts highlight how cultural frameworks—individualism versus collectivism, strong rights-based protections versus pragmatic governance—deeply influence public attitudes toward surveillance. For HCI, this suggests that user perceptions cannot be understood in isolation from their cultural and political environments. Yet despite this recognition, little research has systematically examined international differences in perceptions of traffic surveillance. This study seeks to address that gap by analyzing cross-cultural perspectives on AI-enhanced road monitoring, where questions of privacy, safety, and trust intersect in everyday public life.

3 Methodology

3.1 Study Design and Procedure

Our study employed a mixed 3×3 factorial design, with a between-subjects factor of **region** and a within-subjects factor of **surveillance mode** as the two independent variables (IVs). The regions considered were China, Europe, and the USA. Here, Europe includes the European Economic Area countries plus Switzerland and the UK. The modes of traffic surveillance included: Conventional Surveillance (CS), AI-Enhanced Surveillance (AS), and AI-Enhanced Surveillance with Public Shaming (PS). The dependent variables (DVs) were four measures of participants’ perspectives towards traffic surveillance. See Table 1 for a summary.

Table 1. Summary of study variables.

IV1 - Region	IV2 - Surveillance Mode	DV - Measure
{China, Europe, USA}	{CS, AS, PS}	Perceived {Ability, Risk, Transparency}, Acceptance

Participants were asked to rate all three modes of traffic surveillance using the same set of scale items through an online questionnaire. For each mode (described in subsection 3.2), participants were presented with a picture as visual stimuli and a textual introduction, followed by a set of Likert-scale questions designed to measure four aspects of perception (detailed in subsection 3.3). The display sequence of the modes in the questionnaire was

counterbalanced. The order of the Likert-scale questions within each mode was randomized to reduce potential response bias. Background questions were asked about participants' gender, age, and the country where they had lived the longest in the past decade. Participants were categorized into three regions (China, Europe, and the USA) based on the country they indicated. The estimated time for completion was 5 to 10 minutes. The online questionnaire was offered in both English and Chinese versions. Participants were recruited through various methods, including snowball sampling and online platforms. Only non-identifiable information was collected. The study was approved by the Institutional Review Board of Stanford University.

3.2 Surveillance Modes

The distinction between the three modes of surveillance lies in the way data is analyzed and shared, rather than in the type or storage of the data. All three systems consist of numerous cameras streaming pictures and videos, with multiple monitoring sources displayed simultaneously either to traffic surveillance authorities or on large public screens. The captured video footage is stored on digital servers for a certain period and can be accessed and reviewed later as needed. The description of each system is as follows:

- **Conventional Traffic Surveillance (CS):** Conventional surveillance systems require human operators to manually analyze the data. One or more operators are responsible for monitoring a specific area. If the operators detect a traffic accident, they notify the relevant personnel for handling.
- **AI-Enhanced Traffic Surveillance (AS):** In this system, AI replaces the manual task of analyzing data found in conventional systems. AI automatically analyzes the captured footage, recognizes traffic accidents and rule violations, and identifies relevant information about vehicles and pedestrians (see [Figure 1\(a\)](#)). Security officers then act based on the information provided by the AI.
- **AI-Enhanced Traffic Surveillance with Public Shaming (PS):** This application extends the capabilities of AI by not only recognizing traffic rule violations and identifying relevant personal information through facial recognition technology, but also displaying personal details (e.g., facial photos, names, and IDs) of violators on roadside public screens as a deterrent to future violations (see [Figure 1\(b\)](#)).

3.3 Measures

Participants rated their perspectives of each mode of presented traffic surveillance across four blocks of questions on a 7-point Likert scale ranging from "Strongly disagree" to "Strongly agree". Each block had four question items composing a measure. The four measures were selected based on TAM-VS developed by Krempel and Beyerer [41]: Perceived Capability, Perceived Risk, Perceived Transparency, and Acceptance. The question items were also based on the TAM-VS questionnaire [41], which was modified to suit traffic surveillance systems. The four question items used for each measure are listed below:

- **Perceived Capability (PC):** The perceived usefulness and reliability of the system in ensuring traffic safety in the observed areas. This includes items, namely, "reduce traffic accidents" (PC1), "improve traffic conditions" (PC2), "increase safety" (PC3), and "reliability" (PC4).
- **Perceived Risk (PR):** The perceived risk associated with the system's collection and usage of data. This includes concerns about being disadvantaged by "the processing of the data" (PR1), "the breach of the data" (PR2), "errors in data collection and processing" (PR3), and "the improper use of the data" (PR4).
- **Perceived Transparency (PT):** The perceived transparency of the system, including knowing "the purpose of the system" (PT1), "the type of data collected" (PT2), "how the data will be processed" (PT3), and "who is responsible for the system" (PT4).
- **Acceptance (AC):** The overall acceptance of the system, measured by four items: "I like this system" (AC1), "More systems like this should be used" (AC2), "Such systems should be illegal" (AC3), and "I don't want this system in my city" (AC4).

3.4 Sample and Measure Validity

A total of 720 responses were received. After the initial data screening, 28 unfinished or withdrawn responses were excluded. Additionally, 15 responses from participants residing outside of China, Europe, or the USA were excluded. Furthermore, 76 responses were excluded because the time spent answering the survey was less than 2.5 minutes, which was considered inadequate for a thorough response. Consequently, 601 valid responses were included in the analysis (Europe: $n=201$; China: $n=197$; USA: $n=203$). Figure 6 and Figure 7 present the age and gender distributions by region, providing an overview of the sample's demographics. As the distributions are uneven across regions, we account for these effects in the statistical analysis (see subsection 4.1).

The reliability of the questionnaire was initially tested with the following coefficients: Confidence Intervals (CI), Cronbach's Alpha, and Guttman's Lambda-6. CI for reliability refers to the range of values within which the true reliability of a measurement instrument is likely to fall. Cronbach's alpha assesses the extent to which items within a scale are correlated with one another, indicating the internal consistency of the scale [68]. Guttman's lambda-6 assesses the extent to which items in a scale can be summed or ordered to reflect a single underlying dimension. Cronbach's alpha assumes equal weighting for all items, while Guttman's Lambda-6 does not [34]. These coefficients were calculated using `alpha()` from the `psych` package in R [63]. In this study, all coefficients were within the acceptable range (see Table 6 in Appendix for details), indicating good reliability of the scales.

4 Results

4.1 Statistical Analyses and Overview

Statistical analyses were performed through R version 4.5.1 [63]. To analyze the effects of Mode and Region on measures, linear mixed-effects models (LMEs) were conducted using the `lme4` package [12]. The models included Mode as a within-subjects factor, Region as a between-subjects factor, and their interaction term as fixed effects. Gender and Age were included as covariates to control for their potential influence. P-values for the fixed effects were obtained using Satterthwaite's method for degrees of freedom approximation, as implemented in the `lmerTest` package [42]. Post-hoc comparisons were performed using estimated marginal means with a Tukey adjustment for multiple comparisons via the `emmeans` package [46]. An alpha level of .05 was used for all statistical tests. We decided to report partial eta squared as the estimate of effect size of fixed effects, denoted as η_p^2 , which is interpreted as small effect size (0.01), medium effect size (0.06), or large effect size (0.14) [66]; and Cohen's d as a measure of effect size of simple effects multiple comparisons, denoted as d , which is interpreted as small effect size (0.2), medium effect size (0.5), or large effect size (0.8) [21]. Partial eta squared and Cohen's d were calculated via the `effectsize` package [13].

4.2 Perceived Capability

Figure 2 shows the predicted ratings (adjusted for age and gender) of perceived capability for three traffic surveillance modes across three regions. The main effects of region ($F(2, 595) = 37.58, p < .001, \eta_p^2 = 0.11$) and mode ($F(2, 1196) = 77.58, p < .001, \eta_p^2 = 0.11$) on perceived capability were both statistically significant. The interaction effect was also significant ($F(4, 1196) = 15.29, p < .001, \eta_p^2 = 0.05$). The effect of age was significant but extremely weak ($F(1, 595) = 5.70, p = .017, \eta_p^2 = 0.009$), the effect of gender was not significant ($F(3, 594) = 1.05, p = .351$). Simple effects analysis (see Table 2 for values of means and their standard errors [SE]) indicated the following:

4.2.1 Regional comparisons under mode conditions. Chinese participants rated the perceived capability of all three modes significantly higher than both European participants (CS: $p < .001, d = 0.62$; AS: $p < .001, d = 1.11$; PS: $p < .001, d = 1.50$) and American participants (CS: $p = .006, d = 0.51$; AS: $p < .001, d = 1.24$; PS: $p < .001, d = 1.48$).

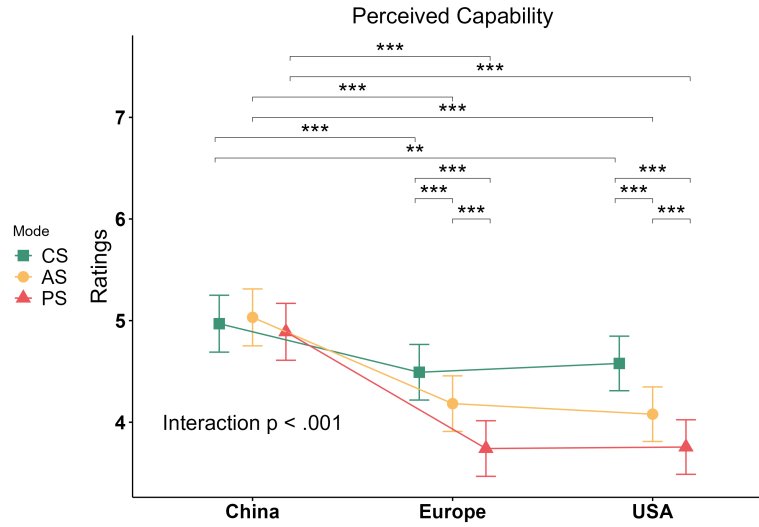


Fig. 2. Interaction plot of Perceived Capability with error bars (95% confidence interval); simple effects are indicated with asterisks: * for $p < .05$, ** for $p < .01$, and *** for $p < .001$. (CS = conventional surveillance; AS = AI-enhanced surveillance; PS = AI-enhanced surveillance with public shaming.)

Table 2. Estimated Marginal Means – Perceived Capability

	China		Europe		USA	
	Mean	SE	Mean	SE	Mean	SE
CS	4.96	0.14	4.49	0.14	4.58	0.14
AS	5.03	0.14	4.18	0.14	4.08	0.14
PS	4.89	0.14	3.74	0.14	3.76	0.14

There were no significant differences between European and American participants in their ratings of the three surveillance modes.

4.2.2 Comparisons of modes within each region. Within Europe, participants rated CS significantly higher than both AS ($p < .001$, $d = 0.40$) and PS ($p < .001$, $d = 0.98$); and AS was rated significantly higher than PS ($p < .001$, $d = 0.58$). Likewise, within the USA, participants rated CS significantly higher than both AS ($p < .001$, $d = 0.65$) and PS ($p < .001$, $d = 1.07$); and AS was rated significantly higher than PS ($p < .001$, $d = 0.42$). In contrast, there were no significant differences in ratings among the three modes within China.

4.3 Perceived Risk

Figure 3 shows the ratings of perceived risk for three traffic surveillance modes across three regions. The main effects of region ($F(2, 595) = 13.88$, $p < .001$, $\eta_p^2 = 0.04$) and mode ($F(2, 1196) = 179.28$, $p < .001$, $\eta_p^2 = 0.23$) on perceived risk were both statistically significant. The interaction effect was also significant ($F(4, 1196) = 25.75$, $p < .001$, $\eta_p^2 = 0.08$). The effect of age ($F(1, 595) = 0.67$, $p = .418$) and gender ($F(3, 595) = 0.38$, $p = .686$) were not

significant. Simple effects analysis (see Table 3 for values of means and their standard errors [SE]) indicated the following:

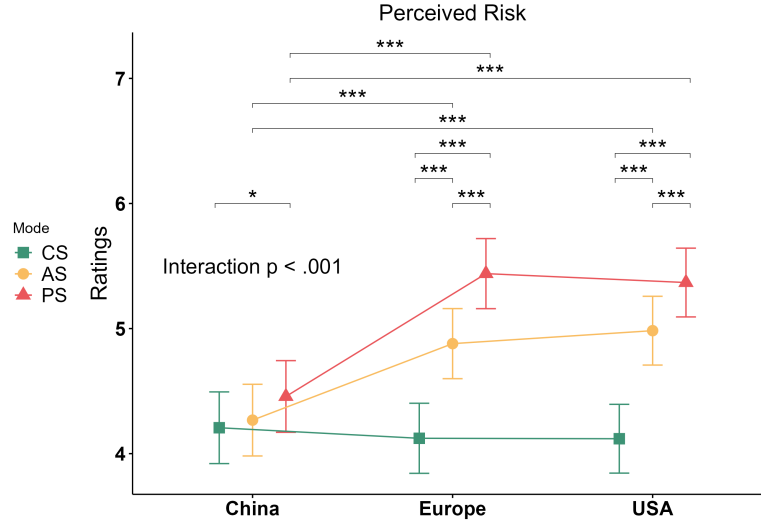


Fig. 3. Interaction plot of Perceived Risk with error bars (95% confidence interval); simple effects are indicated with asterisks: * for $p < .05$, ** for $p < .01$, and *** for $p < .001$. (CS = conventional surveillance; AS = AI-enhanced surveillance; PS = AI-enhanced surveillance with public shaming.)

Table 3. Estimated Marginal Means – Perceived Risk

	China		Europe		USA	
	Mean	SE	Mean	SE	Mean	SE
CS	4.21	0.15	4.12	0.14	4.12	0.14
AS	4.27	0.15	4.88	0.14	4.98	0.14
PS	4.46	0.15	5.44	0.14	5.37	0.14

4.3.1 Regional comparisons under mode conditions. Chinese participants rated the perceived risk of AS and PS significantly lower than both European participants (AS: $p < .001$, $d = 0.71$; PS: $p < .001$, $d = 1.14$) and American participants (AS: $p < .001$, $d = 0.83$; PS: $p < .001$, $d = 1.05$). There were no significant differences between European and American participants in their ratings of the three surveillance modes.

4.3.2 Comparisons of modes within each region. Within Europe, participants rated CS significantly lower than both AS ($p < .001$, $d = 0.88$) and PS ($p < .001$, $d = 1.52$); and AS was rated significantly lower than PS ($p < .001$, $d = 0.65$). Likewise, within the USA, participants rated CS significantly lower than both AS ($p < .001$, $d = 1.00$) and PS ($p < .001$, $d = 1.44$); and AS was rated significantly lower than PS ($p < .001$, $d = 0.45$). Within China, participants rated PS significantly higher than CS ($p = .012$, $d = 0.29$).

4.4 Perceived Transparency

Figure 4 shows the ratings of perceived transparency for three traffic surveillance modes across three regions. The main effects of region ($F(2, 595) = 26.10, p < .001, \eta_p^2 = 0.08$) and mode ($F(2, 1196) = 120.46, p < .001, \eta_p^2 = 0.17$) on perceived transparency were both statistically significant. The interaction effect was also significant ($F(4, 1196) = 34.00, p < .001, \eta_p^2 = 0.10$). The effect of age was significant but extremely weak ($F(1, 595) = 4.54, p = .034, \eta_p^2 = 0.008$), the effect of gender was not significant ($F(3, 595) = 1.34, p = .163$). Simple effects analysis (see Table 4 for values of means and their standard errors [SE]) indicated the following:

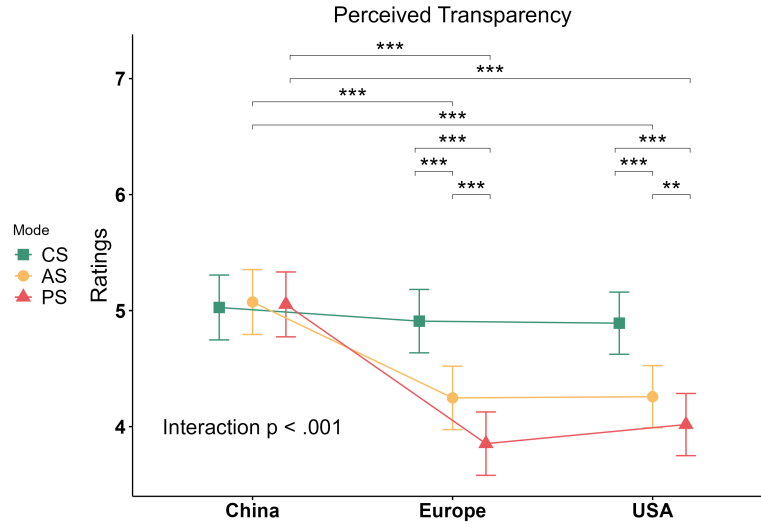


Fig. 4. Interaction plot of Perceived Transparency with error bars (95% confidence interval); simple effects are indicated with asterisks: * for $p < .05$, ** for $p < .01$, and *** for $p < .001$. (CS = conventional surveillance; AS = AI-enhanced surveillance; PS = AI-enhanced surveillance with public shaming.)

Table 4. Estimated Marginal Means – Perceived Transparency

	China		Europe		USA	
	Mean	SE	Mean	SE	Mean	SE
CS	5.02	0.14	4.91	0.14	4.89	0.14
AS	5.07	0.14	4.25	0.14	4.26	0.14
PS	5.05	0.14	3.85	0.14	4.02	0.14

4.4.1 Regional comparisons under mode conditions. Chinese participants rated the perceived transparency of AS and PS modes significantly higher than both European participants (AS: $p < .001, d = 1.15$; PS: $p < .001, d = 1.67$) and American participants (AS: $p < .001, d = 1.13$; PS: $p < .001, d = 1.44$). There were no significant differences between European and American participants in their ratings of the three surveillance modes.

4.4.2 Comparisons of modes within each region. Within Europe, participants rated CS significantly higher than both AS ($p < .001$, $d = 0.92$) and PS ($p < .001$, $d = 1.47$); and AS was rated significantly higher than PS ($p < .001$, $d = 0.55$). Likewise, within the USA, participants rated CS significantly higher than both AS ($p < .001$, $d = 0.88$) and PS ($p < .001$, $d = 1.21$); and AS was rated significantly higher than PS ($p = .002$, $d = 0.33$). In contrast, there were no significant differences in ratings among the three modes within China.

4.5 Acceptance

Figure 5 shows the ratings of acceptance for three traffic surveillance modes across three regions. The main effects of region ($F(2, 595) = 39.46$, $p < .001$, $\eta_p^2 = 0.12$) and mode ($F(2, 1196) = 244.41$, $p < .001$, $\eta_p^2 = 0.29$) on acceptance were both statistically significant. The interaction effect was also significant ($F(4, 1196) = 45.47$, $p < .001$, $\eta_p^2 = 0.13$). The effect of age ($F(1, 595) = 3.20$, $p = .074$) and gender ($F(3, 595) = 0.32$, $p = .723$) were not significant. Simple effects analysis (see Table 5 for values of means and their standard errors [SE]) indicated the following:

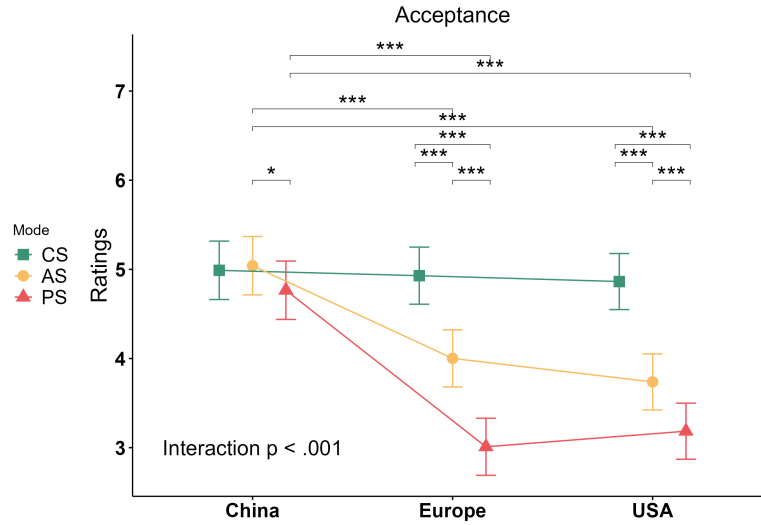


Fig. 5. Interaction plot of Acceptance with error bars (95% confidence interval); simple effects are indicated with asterisks: * for $p < .05$, ** for $p < .01$, and *** for $p < .001$. (CS = conventional surveillance; AS = AI-enhanced surveillance; PS = AI-enhanced surveillance with public shaming.)

Table 5. Estimated Marginal Means – Acceptance

	China		Europe		USA	
	Mean	SE	Mean	SE	Mean	SE
CS	4.99	0.17	4.93	0.16	4.86	0.16
AS	5.04	0.17	4.00	0.16	3.74	0.16
PS	4.77	0.17	3.01	0.16	3.18	0.16

4.5.1 Regional comparisons under mode conditions. Chinese participants rated the acceptance of AS and PS modes significantly higher than both European participants (AS: $p < .001$, $d = 1.04$; PS: $p < .001$, $d = 1.76$) and American participants (AS: $p < .001$, $d = 1.30$; PS: $p < .001$, $d = 1.58$).

4.5.2 Comparisons of modes within each region. Within Europe, participants rated CS significantly higher than both AS ($p < .001$, $d = 0.93$) and PS ($p < .001$, $d = 1.92$); and AS was rated significantly higher than PS ($p < .001$, $d = 0.99$). Likewise, within the USA, participants rated CS significantly higher than both AS ($p < .001$, $d = 1.13$) and PS ($p < .001$, $d = 1.68$); and AS was rated significantly higher than PS ($p < .001$, $d = 0.55$). Within China, participants rated AS significantly higher than PS ($p = .017$, $d = 0.28$).

4.6 Summary of Key Findings

In the following, we summarize the key findings and discuss the causes and implications in the next section.

For conventional surveillance (CS), there are no regional differences in perceived risk, transparency, or acceptance. Overall, AI-powered surveillance (AS and PS) was rated less acceptable with lower capability, higher risk and lower transparency than conventional surveillance (CS). Across all cultures, public-shaming surveillance (PS) is perceived as the riskiest and least acceptable mode.

Chinese participants reported smaller differences between the three surveillance modes, whereas European and American participants showed more pronounced distinctions between the modes. There are no significant differences between Europe and the USA, except that AS is slightly more accepted in Europe than in the USA. AI-powered surveillance (AS and PS) is viewed as more capable, less risky, more transparent, and more accepted in China compared to Europe or the USA.

5 Discussion

5.1 Result Implications

This study advances research on surveillance technology and human–AI interaction by systematically examining how people across different cultural contexts perceive traffic surveillance systems. While prior work has often treated surveillance acceptance as either a technical design challenge (e.g., transparency, privacy-preserving methods) [41, 79] or a cultural question [10, 18, 29] in isolation, our findings reveal the interplay between both. By comparing conventional surveillance (CS), AI-enhanced surveillance (AS), and AI-enhanced surveillance with public shaming (PS) across China, Europe, and the United States, we provide a nuanced view of how AI reshapes public perceptions of road monitoring and how cultural contexts mediate these changes.

5.1.1 Convergent views on conventional surveillance. Much of the HCI literature assumes that cultural differences are the dominant factor in shaping attitudes toward surveillance [18, 82]. Yet our findings show that in the case of conventional surveillance, attitudes converge across regions. Despite China’s more expansive surveillance infrastructure, participants in China, Europe, and the USA shared strikingly similar views on risk, transparency, and acceptance. Although the perceived capability of conventional traffic surveillance (CS) was rated significantly higher by Chinese participants than European and American participants, the magnitude of this difference was noticeably smaller than that observed for the AI-enhanced systems (AS and PS), as shown in Figure 2, which also indicate a convergent view.

This convergence challenges the tendency in prior research to overstate East–West divides and treat cultural context as a catch-all explanation [23, 56]. Instead, our findings suggest that familiarity and standardization may play a more powerful role than cultural orientation in shaping attitudes toward long-standing technologies. For HCI, this calls for a recalibration: rather than assuming cultural difference always drives divergence, we must examine how global infrastructures and decades of exposure can create shared baselines of acceptance.

5.1.2 *AI isn't automatically perceived as an upgrade.* Previous research on “smart” surveillance often emphasizes the promise of AI to improve efficiency, accuracy, and safety [3, 69]. Yet our results show that these benefits are not recognized by the public: European and American participants rated AI surveillance as less capable, more risky, and less transparent than conventional ones, while even Chinese participants did not see AI as more significantly capable than the conventional, as shown in Figure 2.

This challenges the techno-optimism prevalent, which often take for granted that AI is perceived as progress [10]. One of the key reasons to implement AI in traffic surveillance is its potential to significantly enhance security through real-time threat detection and response, as well as to offer improved accuracy while minimizing human error [59]. By centering only on technical capacity, much prior work neglects the perception gap between what AI is supposed to do and what people actually believe it can do. Our findings show that without deliberate efforts to improve AI literacy, communicate tangible benefits, and design for explainability, the public will not automatically trust or prefer AI systems—even when they promise real performance gains.

5.1.3 *Public shaming may not be an acceptable design strategy.* Our findings further demonstrate that public shaming (PS) is widely rejected. In addition to AI-enhanced traffic surveillance being less preferred than conventional surveillance, significant differences were observed between the two AI-enhanced modes studied (AS and PS). European and American participants rated AI-enhanced traffic surveillance with public shaming (PS) as the least preferred across all measures. Although Chinese participants exhibited weaker differences between AS and PS compared to Europeans and Americans, they still perceived PS as significantly higher in risk and lower in acceptance than AS. In contrast, the perceived capability of PS was rated by Chinese participants only on par with AS.

While PS could theoretically serve as a deterrent, participants perceived it as riskier, less acceptable, and no more capable than ordinary AI-enhanced surveillance. The divergence between potential effectiveness and perceived legitimacy highlights a core HCI insight: systems must align with human values, not merely outcomes. This stands in contrast to surveillance practices that emphasize compliance over dignity, such as China's jaywalker-shaming campaigns [30]. Our data suggest that such coercive mechanisms erode trust and increase perceived risks, even when they promise effectiveness. A human-centered approach should instead emphasize positive reinforcement, fairness, and respect for dignity. We argue that PS should be avoided in regulatory frameworks, not only for privacy reasons but also because public rejection undermines its long-term viability.

5.1.4 *Cultural Patterns of Acceptance.* While conventional surveillance elicited convergence, AI-enhanced systems revealed divergence. Chinese participants were more accepting of AI surveillance overall, while Europeans and Americans showed sharper distinctions, favoring CS and rejecting PS. These findings resonate with cultural theory: in collectivist contexts, surveillance may be normalized as a collective good, while individualist contexts place stronger emphasis on privacy and autonomy [14, 43].

Related work has emphasized these cultural divides in abstract terms, but our findings situate them within a concrete infrastructural domain: traffic surveillance. We also note the role of normalization and exposure. China's integration of AI into daily life—from payments to policing—likely shapes participants' higher acceptance. In contrast, Western skepticism is reinforced not only by regulatory debates but also by cultural imaginaries of “AI rebellion” [22] and “AI displacement” [52]. These imaginaries amplify distrust in high-stakes applications like surveillance.

The implication for design and policy is: one-size-fits-all approaches are inadequate. Systems must be tailored to regional expectations—emphasizing efficiency in contexts like China, but prioritizing transparency and accountability in Europe and the U.S. International governance frameworks should therefore balance global principles (fairness, transparency, accountability) with cultural adaptability.

5.1.5 Trust is contextual, not monolithic. Our findings contribute to broader debates about trust in AI. Echoing prior studies [76], we found that European and American participants trust conventional (human-driven) surveillance more than AI-driven alternatives, suggesting a general distrust of AI in high-stakes domains. In contrast, Chinese participants expressed roughly equal levels of trust across all systems. This divergence underscores that trust in AI is both culturally and contextually contingent.

Importantly, trust is not monolithic: participants appear more conservative in domains with direct consequences for safety and rights (e.g., traffic surveillance, healthcare) [19, 70], while tolerating AI more readily in low-stakes or convenience-oriented domains (e.g., chatbots [83], recommender systems [54]). Although previous research found that women are significantly more likely than men to accept public surveillance [55], we did not observe this effect in traffic surveillance, indicating that the context of surveillance matters. For HCI, this highlights the need for domain-specific trust frameworks that account for perceived risk, complexity, and consequences. Policymakers must move beyond blanket AI governance and develop adaptive regulations calibrated to sector-specific stakes.

5.2 Limitations and Future Work

Although our study includes three of the world’s largest entities and economies, namely the USA, China, and Europe, they may not fully represent the perspectives and situations of smaller countries and regions. To gain a more comprehensive understanding across these contexts, future studies should consider including a wider range of countries and regions, particularly those that are less developed, to ensure a more inclusive perspective.

Additionally, this study did not explore intra-regional differences. For instance, Europe is composed of various countries, each with its own local traffic regulations. Similarly, the USA consists of multiple states, each with distinct traffic laws, and China has various provinces and administrative regions, each possibly adapting its own traffic administration practices. This variation in regulations and local practices could result in differing behaviors and perspectives across countries, states, or provinces. Furthermore, there are significant differences between large cities and small towns in terms of traffic conditions, road infrastructure, and population densities. These differences could lead to cultural variations, where local populations may be more pro-technology or pro-privacy. For instance, public shaming in small towns can have dramatically larger and longer-lasting effects on individuals than in larger, more anonymous cities. On the other hand, it may be more intimidating to have your information and traffic violation displayed in Times Square, New York, than at a small town intersection, where there may be few, if any, observers present on the road. Therefore, future studies should consider including intra-regional factors to provide a more nuanced analysis.

We also did not differentiate between whether participants were considering their perspectives as drivers or pedestrians. Although many people are both drivers and pedestrians at different times, their perspectives may vary depending on which role they are currently in. For example, drivers might be more likely to adhere to rules due to their privileged position, whereas pedestrians might have contrasting views due to their vulnerable position on the roadway. The role of AI in traffic surveillance was described in broad terms in the survey, but more specific scenarios could be examined. For instance, the hybridization of AI and human decision-making was not explicitly defined or explored in this study. The extent of AI involvement in decision-making, or whether decisions could be fully automated by AI, are important aspects that may influence individuals’ experiences and could be investigated in future research.

In this study, we did not collect data on participants’ educational backgrounds. This decision was influenced by the requirements of our institution’s data risk management office, which mandated the collection of minimal demographic data. However, we acknowledge that educational background and AI literacy could significantly impact individuals’ experiences with AI, and this is an important factor that should be investigated in future research. Moreover, we only employed a quantitative approach in this study. In future research, a qualitative approach, such as in-depth interviews could be conducted to capture the nuances and complexities of human

experiences and deeper understanding of individual perceptions, attitudes, preferences and concerns about traffic surveillance and AI.

AI-enhanced surveillance is not limited to traffic management; its application in other public venues, such as shopping malls, airports, train stations, and hospitals, presents both unique opportunities and challenges that merit further exploration. These environments may differ significantly from traffic surveillance in their objectives, user interactions, and ethical considerations, as well as differences in power and influence between individuals that share them. For example, drivers can injure pedestrians in ways passers-by in airports can't. Thus, further HCI studies may be necessary to explore these dynamics.

6 Conclusions

Given the global growth in traffic surveillance and recent proposals or pilots supplementing such systems with AI analysis and potentially public shaming, we find it timely to conduct a cross-cultural survey in China, Europe, and the USA to understand road users' perspectives. Regarding conventional road surveillance (cameras only), respondents across regions show comparable assessments of risk, transparency, and acceptance, possibly due to its longstanding presence in all three regions. The addition of AI-enhancement lowers rankings across all scales, including perceived capability, for Europeans and Americans only, while Chinese participants seem to consider the technologies as being more comparable. Yet all three groups similarly ranked AI surveillance with public shaming lower than the other two alternatives. Thus we see significant similarities as well as differences in perspectives across regions. Road users' familiarity with the technology, regional culture and media traditions, alignment with values, trust in AI, and perceptions of benefits may all shape perspectives and contribute to acceptance. For now, people out and about in public are sensitive to having AI eyes on them, even when their role is in support of overall safety.

Acknowledgments

We thank Meagan Loerakker for the early discussions. SY expresses his sincere gratitude to Cecilia Jakobsson Bergstad for her guidance on the methodology. We acknowledge the Wallenberg AI, Autonomous Systems and Software Program – Humanities and Society (WASP-HS). This research was primarily funded by the Marianne and Marcus Wallenberg Foundation.

References

- [1] 2024. Regulation (EU) 2024/1689 of the European Parliament and of the Council of 28 June 2024 on Artificial Intelligence (Artificial Intelligence Act). <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32024R1689> Accessed: 2024-09-09.
- [2] Ahmed S Abdelrahman, Mohamed Abdel-Aty, and Dongdong Wang. 2024. Video-to-Text Pedestrian Monitoring (VTPM): Leveraging Computer Vision and Large Language Models for Privacy-Preserve Pedestrian Activity Monitoring at Intersections. *arXiv preprint arXiv:2408.11649* (2024).
- [3] Victor A. Adewopo, Nelly Elsayed, Zag ElSayed, Murat Ozer, Ahmed Abdelgawad, and Magdy Bayoumi. 2023. A review on action recognition for accident detection in smart city transportation systems. *Journal of Electrical Systems and Information Technology* 10, 1 (2023), 57. doi:10.1186/s43067-023-00124-y
- [4] Vito Albino, Umberto Berardi, and Rosa Maria Dangelico. 2015. Smart cities: Definitions, dimensions, performance, and initiatives. *Journal of urban technology* 22, 1 (2015), 3–21. doi:10.1080/10630732.2014.942092
- [5] Kars Alfrink, Ianus Keller, Neelke Doorn, and Gerd Kortuem. 2023. Contestable Camera Cars: A Speculative Design Exploration of Public AI That Is Open and Responsive to Dispute. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems* (Hamburg, Germany) (CHI '23). Association for Computing Machinery, New York, NY, USA, Article 8, 16 pages. doi:10.1145/3544548.3580984
- [6] Saja Aljuneidi, Wilko Heuten, Larbi Abdenebaoui, Maria K Wolters, and Susanne Boll. 2024. Why the Fine, AI? The Effect of Explanation Level on Citizens' Fairness Perception of AI-based Discretion in Public Administrations. In *Proceedings of the CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) (CHI '24). Association for Computing Machinery, New York, NY, USA, Article 318, 18 pages. doi:10.1145/3613904.3642535

- [7] Saleema Amershi, Dan Weld, Mihaela Vorvoreanu, Adam Fourney, Besmira Nushi, Penny Collisson, Jina Suh, Shamsi Iqbal, Paul N. Bennett, Kori Inkpen, Jaime Teevan, Ruth Kikin-Gil, and Eric Horvitz. 2019. Guidelines for Human-AI Interaction (*CHI '19*). Association for Computing Machinery, New York, NY, USA, 1–13. doi:10.1145/3290605.3300233
- [8] Matthew P. J. Ashby. 2017. The Value of CCTV Surveillance Cameras as an Investigative Tool: An Empirical Analysis. *European Journal of Criminal Policy and Research* 23 (2017), 441–459. doi:10.1007/s10610-017-9341-6
- [9] Booke Auxier and Lee Rainie. 2019. Key Takeaways on Americans' Views About Privacy, Surveillance, and Data Sharing. <https://www.pewresearch.org/short-reads/2019/11/15/key-takeaways-on-americans-views-about-privacy-surveillance-and-data-sharing/>
- [10] Jascha Bareis and Christian Katzenbach. 2022. Talking AI into Being: The Narratives and Imaginaries of National AI Strategies and Their Performative Politics. *Science, Technology, & Human Values* 47, 5 (2022), 855–881. doi:10.1177/01622439211030007
- [11] Bruce G. Batchelor. 1991. Vision and Intelligence. In *Intelligent Image Processing in Prolog*. Springer, London, 1–14. doi:10.1007/978-1-4471-0401-8_1
- [12] Douglas Bates, Martin Mächler, Ben Bolker, and Steve Walker. 2015. Fitting Linear Mixed-Effects Models Using lme4. *Journal of Statistical Software* 67, 1 (2015), 1–48. doi:10.18637/jss.v067.i01
- [13] Mattan S. Ben-Shachar, Daniel Lüdtke, and Dominique Makowski. 2020. effectsizr: Estimation of Effect Size Indices and Standardized Parameters. *Journal of Open Source Software* 5, 56 (2020), 2815. doi:10.21105/joss.02815
- [14] Rod Bond and Peter B. Smith. 1996. Culture and conformity: A meta-analysis of studies using Asch's (1952b, 1956) line judgment task. *Psychological Bulletin* 119, 1 (1996), 111–137. doi:10.1037/0033-2909.119.1.111
- [15] Roger Brooksbank, Jonathan M Scott, and Sam Fullerton. 2022. In-store surveillance technologies: what drives their acceptability among consumers? *The International Review of Retail, Distribution and Consumer Research* 32, 5 (2022), 508–531.
- [16] Anna Brown, Alexandra Chouldechova, Emily Putnam-Hornstein, Andrew Tobin, and Rhema Vaithianathan. 2019. Toward Algorithmic Accountability in Public Services: A Qualitative Study of Affected Community Perspectives on Algorithmic Decision-making in Child Welfare Services. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) (*CHI '19*). Association for Computing Machinery, New York, NY, USA, 1–12. doi:10.1145/3290605.3300271
- [17] British Columbia Canada. [n. d.]. DriveSmartBC. *Social Sciences* ([n. d.]). <https://www.drivesmartbc.ca/aggressive-driving/should-bad-drivers-be-shamed-publicly>
- [18] Chris Chambers. 2015. The Psychology of Mass Government Surveillance: How Do the Public Respond, and Is It Changing Our Behaviour? <https://www.theguardian.com/science/head-quarters/2015/mar/18/the-psychology-of-mass-government-surveillance-how-do-the-public-respond-and-is-it-changing-our-behaviour> Accessed: 2024-08-25.
- [19] Jin Chen, Cheng Chen, Joseph B. Walther, and S Shyam Sundar. 2021. Do you feel special when an AI doctor remembers you? Individuation effects of AI vs. human doctors on user experience. In *Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems*. 1–7.
- [20] Yang Cheng and Hua Jiang. 2020. How Do AI-driven Chatbots Impact User Experience? Examining Gratifications, Perceived Privacy Risk, Satisfaction, Loyalty, and Continued Use. *Journal of Broadcasting & Electronic Media* 64, 4 (2020), 592–614. doi:10.1080/08838151.2020.1834296
- [21] Jacob Cohen. 2013. *Statistical power analysis for the behavioral sciences*. Academic press.
- [22] Alexandra Coman, Benjamin Johnson, Gordon Briggs, and David W Aha. 2017. Social attitudes of AI rebellion: a framework. In *Workshops at the Thirty-First AAAI Conference on Artificial Intelligence*.
- [23] The Economist. 2023. China's Enormous Surveillance State is Still Growing. <https://www.economist.com/china/2023/11/23/chinas-enormous-surveillance-state-is-still-growing> Accessed: 2024-08-25.
- [24] European Parliament. 2024. Artificial Intelligence Act: MEPs Adopt Landmark Law. <https://www.europarl.europa.eu/news/en/press-room/20240308IPR19015/artificial-intelligence-act-meps-adopt-landmark-law> Accessed: 2024-09-09.
- [25] Lawal Ibrahim Dutsinma Faruk, Rohani Rohan, Unhawa Ninrutsirikun, and Debajyoti Pal. 2023. University Students' Acceptance and Usage of Generative AI (ChatGPT) from a Psycho-Technical Perspective. In *Proceedings of the 13th International Conference on Advances in Information Technology* (Bangkok, Thailand) (*IAIT '23*). Association for Computing Machinery, New York, NY, USA, Article 15, 8 pages. doi:10.1145/3628454.3629552
- [26] Steven Feldstein. 2024. Evaluating Europe's push to enact AI regulations: how will this influence global norms? *Democratization* 31, 5 (2024), 1049–1066.
- [27] Xiao Ge, Chunchen Xu, Daigo Misaki, Hazel Rose Markus, and Jeanne L Tsai. 2024. How Culture Shapes What People Want From AI. In *Proceedings of the CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) (*CHI 2024*). Association for Computing Machinery, New York, NY, USA, Article 95, 15 pages. doi:10.1145/3613904.3642660
- [28] Michael Gerlich. 2024. Exploring Motivators for Trust in the Dichotomy of Human—AI Trust Dynamics. *Social Sciences* 13, 5 (2024). <https://www.mdpi.com/2076-0760/13/5/251>
- [29] Thomas Golda, Deborah Guaia, and Verena Wagner-Hartl. 2022. Perception of risks and usefulness of smart video surveillance systems. *Applied Sciences* 12, 20 (2022), 10435.

- [30] David Grossman. 2018. Chinese Facial Recognition System Would Fine Jaywalkers By Text: As opposed to simply displaying information on giant LED screens as happens now. <https://www.popularmechanics.com/technology/infrastructure/a19623846/chinese-facial-recognition-system-would-fine-jaywalkers-by-text/>
- [31] M Guariglia. 2023. *The Impending Privacy Threat of Self-Driving Cars*. <https://www.eff.org/deeplinks/2023/08/impending-privacy-threatself-driving-cars>
- [32] Minjie Guo, Yiheng Liu, Haibin Yu, Binyu Hu, and Ziqin Sang. 2016. An overview of smart city in China. *China Communications* 13, 5 (2016), 203–211. doi:10.1109/CC.2016.7489987
- [33] Nidhi Gupta, Arnout R.H. Fischer, and Lynn J. Frewer. 2012. Socio-psychological determinants of public acceptance of technologies: A review. *Public Understanding of Science* 21, 7 (2012), 782–795. arXiv:<https://doi.org/10.1177/0963662510392485> doi:10.1177/0963662510392485 PMID: 23832558.
- [34] Louis Guttman. 1945. A basis for analyzing test-retest reliability. *Psychometrika* 10, 4 (1945), 255–282. doi:10.1007/BF02288892
- [35] Arun Hampapur, Lisa Brown, Jonathan Connell, Sharat Pankanti, Andrew Senior, and Yingli Tian. 2003. Smart surveillance: Applications, technologies and implications. In *Fourth International Conference on Information, Communications and Signal Processing, 2003 and the Fourth Pacific Rim Conference on Multimedia. Proceedings of the 2003 Joint*, Vol. 2. IEEE, 1133–1138.
- [36] Alyssa Iglar, Auste Simkute, Abigail Sellen, and Mark Chignell. 2024. Getting Back Together: HCI and Human Factors Joining Forces to Meet the AI Interaction Challenge. In *Extended Abstracts of the 2024 CHI Conference on Human Factors in Computing Systems (CHI EA '24)*. Association for Computing Machinery, New York, NY, USA, Article 472, 5 pages. doi:10.1145/3613905.3636285
- [37] Alon Jacovi, Ana Marasović, Tim Miller, and Yoav Goldberg. 2021. Formalizing Trust in Artificial Intelligence: Prerequisites, Causes and Goals of Human Trust in AI (*FAccT '21*). Association for Computing Machinery, New York, NY, USA, 624–635. doi:10.1145/3442188.3445923
- [38] Eunkyung Jo, Daniel A. Epstein, Hyunhoon Jung, and Young-Ho Kim. 2023. Understanding the Benefits and Challenges of Deploying Conversational AI Leveraging Large Language Models for Public Health Intervention. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (Hamburg, Germany) (CHI '23)*. Association for Computing Machinery, New York, NY, USA, Article 18, 16 pages. doi:10.1145/3544548.3581503
- [39] Naveena Karusala, Sohini Upadhyay, Rajesh Veeraraghavan, and Krzysztof Z. Gajos. 2024. Understanding Contestability on the Margins: Implications for the Design of Algorithmic Decision-making in Public Services. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (Honolulu, HI, USA) (CHI '24)*. Association for Computing Machinery, New York, NY, USA, Article 478, 16 pages. doi:10.1145/3613904.3641898
- [40] Mohamad Kashef, Anna Visvizi, and Orlando Troisi. 2021. Smart city as a smart service system: Human-computer interaction and smart city surveillance systems. *Computers in Human Behavior* 124 (11 2021), 106923. doi:10.1016/j.chb.2021.106923
- [41] Erik Krempel and Jürgen Beyerer. 2014. TAM-VS: A Technology Acceptance Model for Video Surveillance. In *Privacy Technologies and Policy*, Bart Preneel and Demosthenes Ikonoumou (Eds.). Springer International Publishing, Cham, 86–100.
- [42] Alexandra Kuznetsova, Per B. Brockhoff, and Rune H. B. Christensen. 2017. lmerTest Package: Tests in Linear Mixed Effects Models. *Journal of Statistical Software* 82, 13 (2017), 1–26. doi:10.18637/jss.v082.i13
- [43] Mei-Po Kwan, Jing Huang, and Zhilin Kan. 2023. People’s political views, perceived social norms, and individualism shape their privacy concerns for and acceptance of pandemic control measures that use individual-level georeferenced data. *International Journal of Health Geographics* 22 (2023), 35. doi:10.1186/s12942-023-00354-3
- [44] Eunhae Lee. 2024. The Power of Perception in Human-AI Interaction: Investigating Psychological Factors and Cognitive Biases that Shape User Belief and Behavior. arXiv:2409.15328 [cs.HC] <https://arxiv.org/abs/2409.15328>
- [45] Min Kyung Lee and Katherine Rich. 2021. Who Is Included in Human Perceptions of AI?: Trust and Perceived Fairness around Healthcare AI and Cultural Mistrust. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems (Yokohama, Japan) (CHI '21)*. Association for Computing Machinery, New York, NY, USA, Article 138, 14 pages. doi:10.1145/3411764.3445570
- [46] Russell V. Lenth. 2025. *emmeans: Estimated Marginal Means, aka Least-Squares Means*. doi:10.32614/CRAN.package.emmeans R package version 1.11.2-8.
- [47] Paul Lewis. 2008. Fears over privacy as police expand surveillance project. *The Guardian* 15, September (2008).
- [48] Freda Lewis-Stempel. 2024. New AI cameras being rolled out to catch drivers breaking the law. <https://www.thisismoney.co.uk/money/cars/article-13804185/new-AI-camera-rollouts-ready-catch-drivers-mobile-smartphone-greater-manchester.html> Accessed: 2024-09-09.
- [49] Tianshi Li, Sauvik Das, Hao-Ping (Hank) Lee, Dakuo Wang, Bingsheng Yao, and Zhiping Zhang. 2024. Human-Centered Privacy Research in the Age of Large Language Models (*CHI EA '24*). Association for Computing Machinery, New York, NY, USA, Article 581, 4 pages. doi:10.1145/3613905.3643983
- [50] Weiyl Li. 2024. A Study on Factors Influencing Designers’ Behavioral Intention in Using AI-Generated Content for Assisted Design: Perceived Anxiety, Perceived Risk, and UTAUT. *International Journal of Human-Computer Interaction* 0, 0 (2024), 1–14. doi:10.1080/10447318.2024.2310354

- [51] Alex Jiahong Lu, Cameron Moy, Mark S. Ackerman, Jeffrey Morenoff, and Tawanna R. Dillahunt. 2024. Perceptions of Policing Surveillance Technologies in Detroit: Moving Beyond "Better than Nothing". In *Proceedings of the 2024 ACM Conference on Fairness, Accountability, and Transparency* (Rio de Janeiro, Brazil) (FAccT '24). Association for Computing Machinery, New York, NY, USA, 2022–2032. doi:10.1145/3630106.3659022
- [52] Matthijs M Maas. 2019. International law does not compute: Artificial intelligence and the development, displacement or destruction of the global legal order. *Melbourne Journal of International Law* 20, 1 (2019), 29–57.
- [53] Mary Madden and Lee Rainie. 2015. *Americans' Attitudes About Privacy, Security, and Surveillance*. <https://www.pewresearch.org/internet/2015/05/20/americans-attitudes-about-privacy-security-and-surveillance/>
- [54] Akihiro Maehigashi, Yosuke Fukuchi, and Seiji Yamada. 2023. Experimental Investigation of Human Acceptance of AI Suggestions with Heatmap and Pointing-based XAI. In *Proceedings of the 11th International Conference on Human-Agent Interaction* (Gothenburg, Sweden) (HAI '23). Association for Computing Machinery, New York, NY, USA, 291–298. doi:10.1145/3623809.3623834
- [55] Jody Messick. 2023. The Impact of Gender on the Acceptance of Surveillance Technology. *Sigma: Journal of Political and International Studies* 40, 1 (2023). <https://scholarsarchive.byu.edu/sigma/vol40/iss1/7>
- [56] Paul Mozur. 2018. Inside China's Dystopian Dreams: A.I., Shame and Lots of Cameras. <https://www.nytimes.com/2018/07/08/business/china-surveillance-technology.html> Accessed: 2024-08-25.
- [57] Taewoo Nam and Theresa A. Pardo. 2011. Conceptualizing smart city with dimensions of technology, people, and institutions. In *Proceedings of the 12th Annual International Digital Government Research Conference: Digital Government Innovation in Challenging Times* (College Park, Maryland, USA) (dg.o '11). Association for Computing Machinery, New York, NY, USA, 282–291. doi:10.1145/2037556.2037602
- [58] Tanya Nazaretsky, Paola Mejia-Domenzain, Vinitra Swamy, Jibril Frej, and Tanja Käser. 2024. AI or Human? Evaluating Student Feedback Perceptions in Higher Education. In *Technology Enhanced Learning for Inclusive and Equitable Quality Education*, Rafael Ferreira Mello, Nikol Rummel, Ioana Jivet, Gerti Pishtari, and José A. Ruipérez Valiente (Eds.). Springer Nature Switzerland, Cham, 284–298.
- [59] Forbes Technology Council Nick Herbert. 2023. Intelligent Surveillance As A Tool For Social Good. <https://www.forbes.com/councils/forbestechcouncil/2023/11/02/intelligent-surveillance-as-a-tool-for-social-good/> Accessed: 2024-08-14.
- [60] ONHCR. 2022. *Spyware and surveillance: Threats to privacy and human rights growing, UN report warns*. <https://www.ohchr.org/en/press-releases/2022/09/spyware-and-surveillance-threats-privacy-and-human-rights-growing-un-report>
- [61] Tatiana Ortegon-Sarmiento, Patricia Paderewski, Francisco Gutierrez-Vela, Souso Kelouwani, and Alvaro Uribe-Quevedo. 2022. Case study on technological acceptance of autonomous vehicles and the influence of situational awareness: Lane detection in winter conditions. In *Proceedings of the XXII International Conference on Human Computer Interaction* (Teruel, Spain) (Interacción '22). Association for Computing Machinery, New York, NY, USA, Article 15, 4 pages. doi:10.1145/3549865.3549906
- [62] Boris Pokrić, Srđan Krčo, Maja Pokrić, Petar Knežević, and Dejan Jovanović. 2015. Engaging citizen communities in smart cities using IoT, serious gaming and fast markerless Augmented Reality. In *2015 International Conference on Recent Advances in Internet of Things (RIoT)*. 1–6. doi:10.1109/RIOT.2015.7104905
- [63] R Core Team. 2023. *About R: What is R?* <https://www.r-project.org/about.html> Accessed: 2024-08-14.
- [64] Md Arafatur Rahman, A Taufiq Asyhari, LS Leong, GB Satrya, M Hai Tao, and MF Zolkipli. 2020. Scalable machine learning-based intrusion detection system for IoT-enabled smart cities. *Sustainable Cities and Society* 61 (10 2020), 102324. doi:10.1016/j.scs.2020.102324
- [65] Joel R Reidenberg. 2015. The transparent citizen. *Loy. U. Chi. LJ* 47 (2015), 437.
- [66] John T.E. Richardson. 2011. Eta squared and partial eta squared as measures of effect size in educational research. *Educational Research Review* 6, 2 (2011), 135–147. doi:10.1016/j.edurev.2010.12.001
- [67] Ronald Reagan Presidential Library and Museum. n.d.. Constitutional Amendments: Amendment 4 – Right to Privacy. <https://www.reaganlibrary.gov/constitutional-amendments-amendment-4-right-privacy> Accessed: 2024-09-09.
- [68] Neal Schmitt. 1996. Uses and abuses of coefficient alpha. *Psychological Assessment* 8, 4 (1996), 350–353. doi:10.1037/1040-3590.8.4.350
- [69] Himani Sharma and Navdeep Kanwal. 2024. Video surveillance in smart cities: current status, challenges & future directions. *Multimedia Tools and Applications* (2024), 1–46. doi:10.1007/s11042-024-19696-6
- [70] Venkatesh Sivaraman, Leigh A Bukowski, Joel Levin, Jeremy M. Kahn, and Adam Perer. 2023. Ignore, Trust, or Negotiate: Understanding Clinician Acceptance of AI-Based Treatment Recommendations in Health Care. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems* (Hamburg, Germany) (CHI '23). Association for Computing Machinery, New York, NY, USA, Article 754, 18 pages. doi:10.1145/3544548.3581075
- [71] Ian René Solano-Kamaiko, Dibyendu Mishra, Nicola Dell, and Aditya Vashistha. 2024. Explorable Explainable AI: Improving AI Understanding for Community Health Workers in India. In *Proceedings of the CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) (CHI '24). Association for Computing Machinery, New York, NY, USA, Article 399, 21 pages. doi:10.1145/3613904.3642733
- [72] S Shyam Sundar. 2020. Rise of Machine Agency: A Framework for Studying the Psychology of Human–AI Interaction (HAI). *Journal of Computer-Mediated Communication* 25, 1 (01 2020), 74–88. doi:10.1093/jcmc/zmz026

- [73] Khoa Tran, Tuyet Nguyen, Linh Phan, My Tran, Mai Trinh, and Linh Pham. 2022. Stakeholders' attitudes towards the installations of closed-circuit television cameras in reducing school violence. *Heliyon* 8, 9 (2022).
- [74] European Union. 2016. General Data Protection Regulation (GDPR). <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32016R0679> Regulation (EU) 2016/679 of the European Parliament and of the Council.
- [75] U.S. News and World Report. 2021. States Push Back Against Use of Facial Recognition by Police. *U.S. News and World Report* (2021). <https://www.usnews.com/news/politics/articles/2021-05-05/states-push-back-against-use-of-facial-recognition-by-police> Accessed: 2024-09-07.
- [76] E. S. Vorm and David J. Y. Combs. 2022. Integrating Transparency, Trust, and Acceptance: The Intelligent Systems Technology Acceptance Model (ISTAM). *International Journal of Human-Computer Interaction* 38, 18-20 (2022), 1828–1845. doi:10.1080/10447318.2022.2070107
- [77] Ziming Wang, Ziyi Hu, Björn Rohles, Sara Ljungblad, Vincent Koenig, and Morten Fjeld. 2023. The Effects of Natural Sounds and Proxemic Distances on the Perception of a Noisy Domestic Flying Robot. *ACM Transactions on Human-Robot Interaction* 12, 4, Article 50 (Dec 2023), 32 pages. doi:10.1145/3579859
- [78] Ziming Wang, Meagan B. Loerakker, Yiqian Wu, Shiwei Yang, Arion Pons, Yuwei Chuai, David Sirkin, and Morten Fjeld. 2025. In a Flap: Experiences with a Bioinspired Flying Robot. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 9, 3, Article 138 (Sept. 2025), 20 pages. doi:10.1145/3749495
- [79] Ziming Wang, Yiqian Wu, Shiwei Yang, Xiaowei Chen, Björn Rohles, and Morten Fjeld. 2024. Exploring Intended Functions of Indoor Flying Robots Interacting With Humans in Proximity. In *Proceedings of the CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) (CHI '24). Association for Computing Machinery, New York, NY, USA, Article 264, 16 pages. doi:10.1145/3613904.3642791
- [80] Ziming Wang, Yiqian Wu, Qingxiao Zheng, Shihan Zhang, Ned Barker, and Morten Fjeld. 2025. A Meat-Summer Night's Dream: A Tangible Design Fiction Exploration of Eating Biohybrid Flying Robots. (Preprint).
- [81] Jingyi Xiao and Konstadinos G. Goulias. 2022. Perceived usefulness and intentions to adopt autonomous vehicles. *Transportation Research Part A: Policy and Practice* 161 (2022), 170–185. doi:10.1016/j.tra.2022.05.007
- [82] Qian Yang, Richmond Y. Wong, Steven Jackson, Sabine Junginger, Margaret D. Hagan, Thomas Gilbert, and John Zimmerman. 2024. The Future of HCI-Policy Collaboration. In *Proceedings of the CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) (CHI '24). Association for Computing Machinery, New York, NY, USA, Article 820, 15 pages. doi:10.1145/3613904.3642771
- [83] Jordyn Young, Laala M Jawara, Diep N Nguyen, Brian Daly, Jina Huh-Yoo, and Afsaneh Razi. 2024. The Role of AI in Peer Support for Young People: A Study of Preferences for Human-and AI-Generated Responses. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. 1–18.
- [84] Sol Hee Yoon Young Woo Kim, Min Chul Cha and Seul Chan Lee. 2024. Not Merely Useful but Also Amusing: Impact of Perceived Usefulness and Perceived Enjoyment on the Adoption of AI-Powered Coding Assistant. *International Journal of Human-Computer Interaction* 0, 0 (2024), 1–13. doi:10.1080/10447318.2024.2375701
- [85] Peng Zhang, Tony Thomas, Sabu Emmanuel, and Mohan S. Kankanhalli. 2010. Privacy preserving video surveillance using pedestrian tracking mechanism. In *Proceedings of the 2nd ACM workshop on Multimedia in forensics, security and intelligence, MiFor@MM 2010, Firenze, Italy, October 29, 2010*, Sebastiano Battiato, Sabu Emmanuel, Adrian Ulges, and Marcel Worring (Eds.). ACM, 31–36. doi:10.1145/1877972.1877983
- [86] Pete Zrioka. 2022. ASU Entrepreneurs Develop Smart Street Cameras. <https://news.asu.edu/20220719-entrepreneurship-asu-entrepreneurs-develop-smart-street-cameras> Accessed: 2024-08-09.

A Appendix

Table 6. Reliability values of the four question items: PC, PR, PT, and AC.

Question items	95% CI	Cronbach's α	Guttman's λ
Perceived Capability (PC)	Feldt: [0.87, 0.89] Duhachek: [0.87, 0.89]	0.88	0.86
Perceived Risk (PR)	Feldt: [0.88, 0.90] Duhachek: [0.88, 0.90]	0.89	0.86
Perceived Transparency (PT)	Feldt: [0.86, 0.88] Duhachek: [0.86, 0.88]	0.87	0.84
Acceptance (AC)	Feldt: [0.94, 0.95] Duhachek: [0.94, 0.95]	0.95	0.93

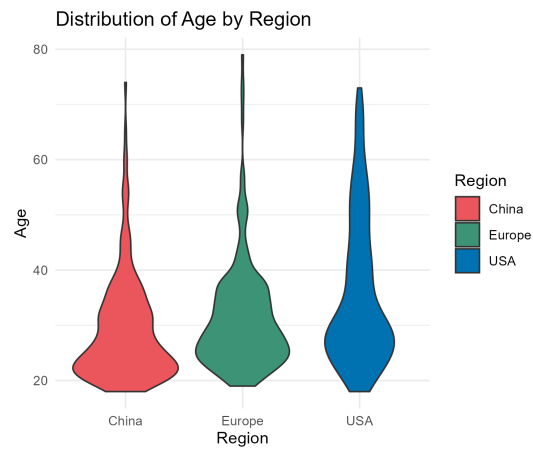


Fig. 6. The distribution of age by region.

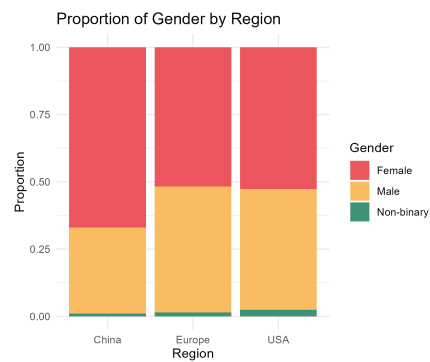


Fig. 7. The distribution of gender by region.