Public Drone: Attitude Towards Drone Capabilities in Various Contexts

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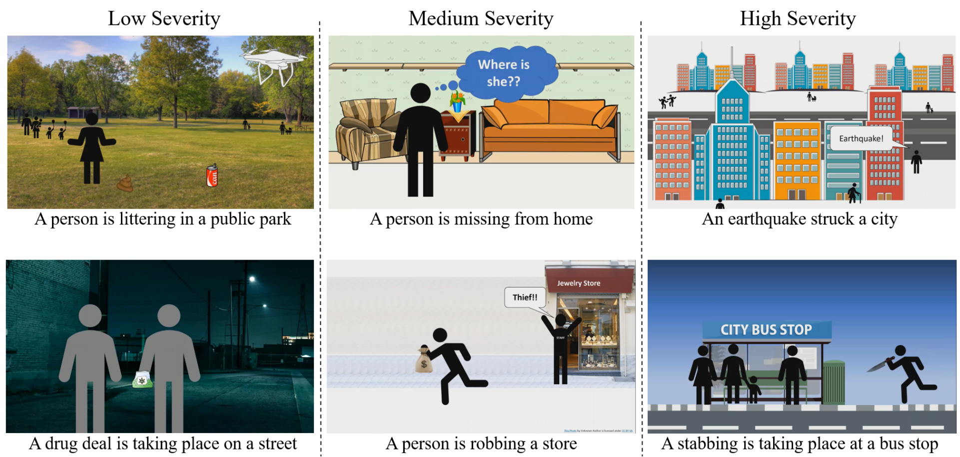

Figure 1: Example of use cases for public drones with three different levels of context severity: low, medium, and high; derived from the results of the pre-study. Each vignette corresponds to a screenshot taken from video clips used in an online survey to evaluate people's attitude towards drone capabilities for each context of use.

ABSTRACT

Drone technologies represent a new category of mobile devices that are increasingly present in public spaces. They are becoming increasingly autonomous, featuring a wide range of capabilities from detecting objects to monitoring situations. Yet, little is known about the characteristics that influence their acceptability in public spaces. In this work, we investigate how people's attitude towards drone capabilities is influenced by the context in which they are operating. We present three user studies: first, a participatory design study (N=5) in which we investigated people's expectations towards drone capabilities and contexts of use; second, a pre-study (N=18) performed to select 6 contexts of use for public drones with three different severity levels; and third, a survey-based study (N=26) where we evaluated people's attitude towards 10 drone capabilities in 6 contexts of varying severity levels. Our results demonstrate that people's attitude towards drone capabilities is more positive for severe contexts. In addition, we found positive correlations for all capabilities between attitude and perceived severity of context. This work contributes to the design of context-sensitive human-drone interactions and to the future integration of public drones.

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CCS CONCEPTS

• **Human-centered computing** → **Empirical studies in HCI**; **Ubiquitous and mobile devices**; • **Computer systems organization** → *Robotics*.

KEYWORDS

Human-Drone Interaction; Drone; UAV; Capabilities; Context; Attitude; Acceptability; Ubiquitous Computing; Public Spaces.

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1 INTRODUCTION

Over the last few years, and more specifically over the last year amidst the COVID-19 crisis, we have been witnessing a revolution in the field of aerial robotics where drones became ubiquitous to human environments [11, 24, 65]. They represent versatile mobile technologies, used in daily life for both leisure and professional activities (e.g., deliveries [58]). Their high availability and affordability helped increase the number and type of scenarios of use [37] and recent works have explored the use of drones in cities, such in pedestrian guidance [16] or search and rescue operations [46]. Moreover, drones can serve as flexible mobile platforms for smart cities, with the potential to tremendously improve public safety in future urban areas [27] and increase people's life quality. Such public drones could support people by walking them home safely at night [31], helping them navigate to a free parking spot [45], facilitating quick contact with medical services or the police [65], and even assisting vulnerable populations such as people with disabilities [7, 28]. Future applications could further consider helping people, such as in assisting elderly populations, as suggested by prior works [19, 42], or in expanding the use of a navigation drone [6] to find a lost dog or car for example.

Despite the rich range of potential applications for public drones, there is a plethora of obstacles to overcome to facilitate their acceptability in public spaces [15]. Indeed, lack of acceptability can profoundly affect the overall user experience [66] and can lead to negative feelings towards scenarios in which this technology is involved [34]. For example, prior research showed that low acceptability can result in vandalism against public robots, which may, not only damage the robot, but also result in the aggressor being hurt [51]. Therefore, technology acceptability (or acceptance) is "a central viewpoint to understanding the human aspects of interactive systems" [33], and we observe a growing interest from the community in designing socially acceptable human-machine interactions [47]. Unfortunately, despite its high relevance, there are no established methods for evaluating such acceptability [32]; and acceptability of systems has often been determined through attitude evaluations [54], based on the socio-psychological attitude theory of planned behavior [1]. Attitude can be defined as an evaluation of an entity along a continuum from disfavor to favor and moreover predicts behavioral intentions [3]. Finally, prior research showed that attitude and a priori acceptability were correlated [44].

We propose that factors shaping and contributing to public acceptability of drones should be further investigated to create likeable and unintrusive ways to integrate public drones into human urban spaces. While various factors will contribute to acceptability of drones in public spaces, such as privacy, which is one of the main concerns of people fearing intrusion into their private spheres [12, 35]; other factors may also moderate this acceptability. We here focus on the perceived severity of context – defined as the perceived severity of harm if no action is taken [63] – which was shown to influence behavioral intention to use protective technology [13], such as embodied by public drones.

This paper first presents a literature survey of drones in public spaces, their acceptability, as well as theories and measurements of attitudes and acceptability towards technologies. We continue by describing an exploratory Participatory Design (PD) study (N=5) on police drones, as an instance of public drones as to narrow the scope of this exploratory first step, and findings gained from it. We then describe a pre-study (N=18) performed to select six contexts (i.e., different situations) of use for public drones, with three different severity levels from a list based upon the PD study results. We then present an online survey (N=26) designed to explore people's attitude towards drone capabilities for each context. After presenting the survey results, we conclude with a discussion of our findings and insights for future research. To the best of our knowledge, this work is the first to investigate the influence of the severity of context on human attitude towards public drone capabilities. Our work contributes in the following:

- Results of a user study (N=26) demonstrating how people's attitude towards drone capabilities is shaped by the severity of context in which they are presented
- A range of validated contexts of different severity levels and acceptable capabilities for public drones

2 RELATED WORK

This section presents prior work related to drones in public spaces, as well as more general research conducted on the acceptability of drones in human spaces, and existing methodologies to measures of acceptability.

2.1 Drones in Public Spaces

Drones have already started populating our skies. Initially used as mobile personal technologies, such as for people to take photos and videos, they are becoming increasingly autonomous and capable of performing complex tasks. We expect that, in the future, smart cities will feature automated drones as shared mobile technologies, that are part of the city ecosystem. Such urban drones have already been researched for a wide range of applications from simple delivery [58] to more complex ways of supporting people's lives. Drones have been envisioned as pervasive displays [55, 56], providing guidance to pedestrians [16], or even navigating drivers to a parking spot [45]. They have also been used as tour guides [9], safety features [31], agents to support a clean environment [43], traffic enforcement [48], and more widely for safety and security [27], as well as emergency and search and rescue [30], or in police work [4]. Despite their potential to improve our lives, prior work showed a general lack of knowledge from the public, so that out of a list of forty different applications, people were not aware of the majority of current and future drone applications [8]. This work also showed that there is much reservation on the use of drones for public service. This is also due to the perceived privacy intrusiveness of drones [12] that people perceive as able to record without consent. Yet, Aydin [8] further pointed out to misconceptions on the actual drone capabilities and demonstrated that only 60% of the general public – in the US – knew that not all drones have cameras. This complements prior research, which showed that people tend to assign different features and capabilities to drones based on their physical properties and overall design with sometimes discrepancies between the drone actual and perceived capabilities [68]. This alludes to the fact that different capabilities might be perceived differently. As such, we propose to investigate the acceptability of different public drone capabilities. The next section describes prior research on the acceptability of drones in public spaces.

2.2 Acceptability of Drones in Public Spaces

The long lasting adoption and positive impact of drone technology will depend on its acceptability by the general public [35, 48], and in particular the relevance to its context of use. In particular, Lidynia et al. [35] highlighted the importance of the context of deployment on people's acceptance of drones, so that different types of usage (e.g., hobby, commercial, emergency) result in different requirements in terms of what the drone should look like or how it should fly. Aydin [8] further showed that people's support for public safety and scientific drones were significantly higher than people's support for commercial and hobby usage. In most works on the topic of drone acceptability, people's main concerns appeared to be privacy and safety [8, 12, 35, 48, 72], with different contexts of use revealing different acceptability challenges. In the case of delivery drones, Yoo et al. [72] showed several factors contributing to their acceptance, including the relative advantages of the technology over other solutions (e.g., delivery speed and environmental friendliness); and further discussed perceived risks (i.e., malfunction and privacy) which negatively influence the attitude toward drone delivery. Prior work further investigated people's attitude towards the use of police drones in the US [4] and found individual differences based on the racial composition of the neighbourhood where the drone would be used for surveillance, as well as based on the individual's political affiliation (i.e. liberal vs. conservative). Additional work investigated the perception of traffic enforcement drones [48] and found that participants were more positive towards the use of drones in more severe offenses, such as identifying stolen vehicles and aggressive driving; and less positive towards smaller offenses, such as littering or stop sign violation. These results imply that the drone capabilities may indeed affect people's attitude towards the acceptability of drones in different contexts of use. Furthermore, their work showed cultural differences where the level of approval for the use of traffic enforcement drones was greater in the Israeli than in the US population. These prior research works investigating the factors affecting people's attitude towards drones come from various fields, spanning from social science to aerospace engineering. We here propose to take a human-centered approach to understanding which drone capabilities are acceptable for different contexts of use and severity. The next subsection discusses methodologies to measure attitude and acceptability of technologies.

2.3 Measuring Attitude and Acceptability of Technologies

Several theories and tools have been used in the social psychology literature to measure attitude and acceptability of technologies. Yet, there is a lack of consensus in which tools are best for use in the HCI community [32]. The Technology Acceptance Model (TAM) [17, 18] has been designed to explain and predict technology – initially computer – use, behavior, and adoption, based on two factors: perceived ease of use and usefulness. While it has been used in prior drone research [72], it "lacks explicit consideration of social and normative variables" [73] and is designed towards the technology users, which would not necessarily be the case in public drones which can be experienced by bystanders. Similarly, methods such as the Van der Laan scale [60], also focus on users' dimensions: usability and satisfaction, which are not suited in this work. One of the most widely used approach to defining acceptance is the Theory of Planned Behaviour (TPB) [1], which initially extended the Theory of Reasoned Action (TRA) [23] with added external factors, such as media and social acceptance, and more flexibility towards rapidly changing technologies. TPB considers three components that can predict intention: attitude toward the behavior, subjective norm, and perceived behavioral control; which are then used to derive people's behaviors and acceptability (e.g., in [21]). One drawback to this method is that the resulting questionnaire is complex and lengthy [2], and as such, prior research works often used a decomposed TPB. More recently, the Unified Theory of Acceptance and Use of Technology (UTAUT) [61] combined aspects of prior theories (including TAM and TPB) into four constructs: performance and effort expectancy, social influence, and facilitating conditions. However, UTAUT presents a high number of independent variables. In robotics, Nomura and Kanda [40] developed a tool to measure people's anxiety towards robots, which evolved into the Negative Attitude toward Robots Scale (NARS) [41] and includes three subscales: situations and interactions with robots, social influence of robots, emotions in interaction with robots. This tool has been widely used in the Human-Robot Interaction (HRI) community, including in prior drone research [70], but includes specific scales which are not meant to be adapted to different drone capabilities and contexts of use. In recent research on drone acceptance, Aydin [8] proposed an adaptation of the KAP model: Knowledge, Attitude and Practice, a survey instrument tailored to learning what people know, how they feel, and how they would react about specific items (e.g., drone applications). While this model could be suited to our needs, the questionnaire reliability was not validated, and as such we decided to not use this model. Instead, we preferred to use a validated tool specific to attitude. We therefore opted for the Attitude 4-Item scale (proposed by [59], and based upon TAM, TPB, and Decomposed TPB), which measures the feelings of favorableness or unfavorableness towards using a specific technology with a relatively short measurement tool and good reliability (λ^2=.85).

To address people's attitude towards drone capabilities, we ran a Participatory Design (PD) study focusing on the design of police drones, as examples of public drones, to narrow the scope of this exploratory first step. Police drones were chosen as they are already used in public spaces [36], are discussed richly in prior work [22, 39], and cover a large spectrum of contexts of use, from guidance and communication of important information [65] to more traditional law enforcement [57].

3 EXPLORATORY PARTICIPATORY DESIGN STUDY

Given that prior research showed that the general public tends to be unaware of possible drone applications [8], we decided to run an exploratory PD study to compile: 1. a list of contexts of use for police drones based on people's beliefs, and 2. a list of capabilities suited to each context of use. In addition, this study was used to generate one-fits-all designs representing people's expectations towards the physical representation of such capabilities on drones. We chose a PD approach as it is an important method used in the generation phase of novel artefacts, products, and services; and which can involve both experienced or inexperienced users [70, 71].

3.1 Methodology

We used convenience sampling and recruited 5 participants (3 F, 2 M) (μ= 26.2 y.o., SD= 7.8) for which we obtained verbal consent prior to the study. We ran this exploratory study with each participant individually accompanied by a member of the research team in person, except for one participant that was run remotely. This approach was chosen as individual sessions have been described as best for probing, priming, and understanding applications [52]. The study started with a structured interview followed by a sketching phase and lasted around 30 minutes per participant. This methodology was adapted from prior works using PD with drones, with similar sample size [71] and time-frame [29]. The interviews were audio-recorded, transcribed, and anonymized for thematic analysis. The next subsections describe the methodology used for both the interview and the sketching task.

3.1.1 Interview. The interview was structured in two stages. The first stage consisted in eliciting application and capabilities for police drones. Participants were first asked about events in which a police drone can assist them. Once the event identified, they were asked to consider which capabilities the police drone would need to fulfill its role, within the given event. Finally, they had to justify their answers regarding why each capability would be useful for the given event. This first stage was repeated at least three times for each participant to gather sufficient data such that each participant mentioned at least 3 applications and capabilities for police drones at this stage. In the second stage, participants were presented with a list of five events, inspired from prior research [8, 31]: a demonstration, a robbery, guarding a park, walk me home safely at night, and a terror attack. Participants were asked to choose two out of the five events, also ensuring that they did not already propose this idea in the first stage. Once the events chosen, they were once again asked about the capabilities needed to fulfill this role and to justify their answer for each capability.

3.1.2 Sketching Task. Following the interview, we involved the participants in a sketching task which aimed to gather their perception of the visual representation of the said capabilities in police drones. Participants were handed a sheet of paper with four silhouettes illustrating a drone (quadcopter) from four different angles. Participants were asked to draw a police drone that could help them in all events discussed during the interviews and featuring the named capabilities. The drone silhouettes were provided as a template for people to focus on the capabilities within existing drone structures.

3.2 Findings and Discussion

This section presents the findings of the thematic analysis that followed the interview and which corresponds to the contexts of use and drone capabilities suggested by participants. We further present insights into the designs for police drones gathered from the participants' sketches.

3.2.1 Contexts of Use. We found that participants envisioned police drones supporting them throughout diverse events and contexts of use (see examples in Table 1). In particular, participants anticipated police drones helping people in both daily life (e.g., traffic jam and traffic violations) and emergency situations, both natural events (e.g., fire and earthquake) and man-made ones (e.g., terror attacks), as well as in more traditional police work, monitoring and intervening over illegal actions (e.g., assaults and crimes). Participants further described a shift in today's technological abilities: *"if you thought that before the drone era, you can get away with it if you're fast enough and if your plan is good enough; now you have eyes and ears everywhere"* (P1).

3.2.2 Capabilities. Participants imagined a large range of capabilities for police drones that are illustrated in Table 2. They envisioned the drones would have the ability to report and alert the closest police officers; prevent crimes from happening; or even recognize situations, humans and animals. These chosen capabilities show that people do envision the police drones as intelligent systems capable of making decisions and operating, at least partially, autonomously. Interestingly, while most capabilities show interaction potential, the interaction is always focusing on the drone (e.g., sensing and feedback) and not on the interaction with stakeholders.

Another important finding was that 3 out of 5 participants further envisioned that in emergency situations such as terror attacks, the drones would be capable of using weapons, with abilities ranging from spraying water, tear gas, pepper spray, or even being equipped with a tranquilizer gun: *"The drone could shoot an arrow to paralyze the person"* (P2). P3 proposed a less drastic approach to handling criminals by putting *"a net to capture offenders"* (P3). Participants additionally compared the capabilities of police drones to human officers when assisting in specific events, such as *"you cannot teach your policemen all the faces of criminals but you can teach the drone"* (P1). Some further expressed doubts regarding the usefulness of police drones, such as P5 who explained that a police drone might not entirely prevent crime, but it will give people additional tools to analyze a situation. This shows that the boundaries between drones being considered as tools vs. as individually capable of performing actions are still not well formed in the public opinion.

3.2.3 Visual Representation of Drone Capabilities. In analyzing the sketches, we discovered interesting patterns across participants (see example sketches in Figure 2). We found that all participants decided to clearly identify the drone as a police drone using colors (red and blue). Most of the capabilities mentioned in the interviews were designed to be clearly visible on the drone's body. For example, all participants drew a camera over the drone body to signify that the drone can record videos. We also noticed that some capabilities were consistently omitted in the drawings, such as alerting the police, although this capability was mentioned by all participants, suggesting some level of implicit communication between the drone

Table 1: Examples of events that participants named when asked in which events a police drone could assist in.

Applications	Events & Contexts of use
Tracking	*Prevent criminals to escape* (P1); *Chase in an urban environment* (P3); *Criminal on the run* (P5)
Emergency	*Fire, Missing Person, Stabbing (Terror Attack), Earthquake* (P2)
Illegality	*Burglary, Assault* (P1); *Crime* (P2, P4); *Violent protest, Drug deal* (P3); *Fight* (P4)
Public Gathering	*Demonstration* (P2); *Protest* (P3); *Riot* (P5)
Transportation	*Car accident* (P4); *Traffic jam, Traffic violations* (P5)

Table 2: Examples of participants' quotes when generating ideas for capabilities of police drones in specific events.

Capabilities	Quotes from participants	Part.
Aid & Delivery	*"if it's big it can [...] help taking the person who needs help to a secure place"*	P2
	"Delivery of food and medical supply in places where you usually have no access"	P2
	"provide bandages"	P4
Alert & Report	*"Speed dial to the police"*	P4
	"lead the police there"	P5
Auditory Feedback	*"A siren, a speaker, just to say the police is here"*	P3
	"Speakers to talk and threaten the protestors"	P4
Gathering Evidence	*"record everything that is suspicious"*	P1
	"Recording for proof if something happens"	P3
	"take a picture and then send you the ticket [...] straight to your home"	P5
	"taking evidence from [...] above the scene"	P5
Recognition	*"they could recognize your voice"*	P1
	"It should be able to identify the suspect, target it and follow it automatically"	P3
	"we can teach the drone what to look for"	P5
Weapons	*"Put a net to capture offenders"*	P3
	"The drone could shoot an arrow to paralyze the person"	P2
	"Arm the drone with gas"	P4

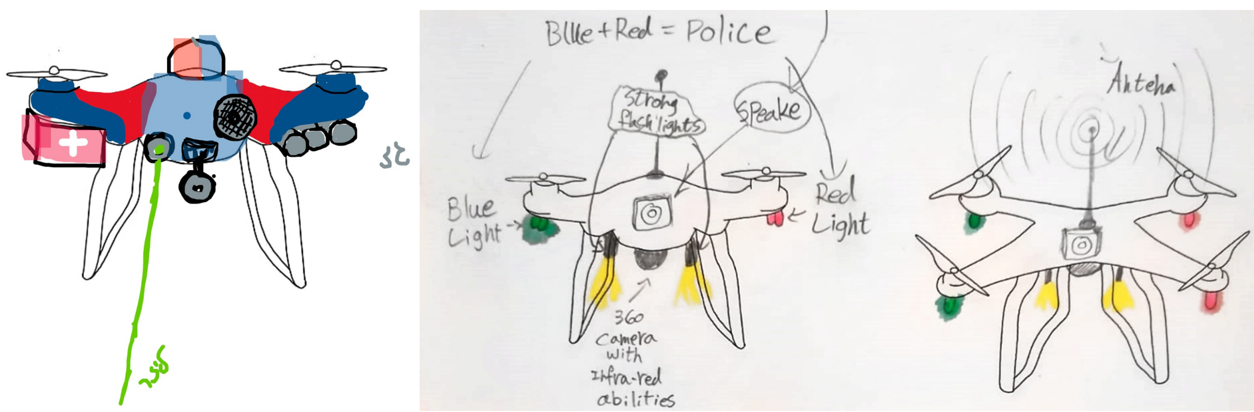

Figure 2: As part of the exploratory PD study, participants were asked to sketch capabilities for police drones used in a variety of events and contexts. Participants were given drone silhouettes displayed at different angles as a starting point. The left and right images present examples sketches. In both cases, the participant clearly identified the drone as a police drone using colors and further added sensors (e.g., cameras) as well as feedback strategies (e.g., lights and speakers on the right sketch).

and the rest of the police forces. A participant further suggested that the drone should adjust its appearance based on the situation *"If it's in the air, you have to have lights on it so people will notice it, but because it's a police drone, sometimes you don't want people to see it"* (P4), representing the varying needs for the drone to perform its tasks.

This exploratory study helped us identify a range of contexts of use and capabilities for police drones based on people's current beliefs. While police drones were used as an instantiation for public drones, we noticed throughout the PD study that police drones seem to be subjected to preconceptions around general police work (e.g., "*now you have eyes and ears everywhere*") (P1). While controversial opinions on police drones [4, 50] provided an interesting basis to generate possible scenarios and capabilities for public drones, they could negatively bias our larger evaluation on acceptability of public drones. Since the proposed applications (Table 1) and capabilities (Table 2) mostly correspond to first responders' work that could be performed by other public entities (e.g., firefighters, emergency medical services), we opted to widen our perspective and continue with a larger interpretation of public drones in the following study.

4 STUDY ON ATTITUDE TOWARDS DRONE CAPABILITIES

The aim of the study was to explore the attitude, "*which reflects feelings of favourableness and unfavourableness*" [59], of people towards ten selected public drone capabilities (Table 3) in six different contexts of use divided in three severity levels (see Figure 1), based on the findings of the PD study.

4.1 Research Question and Hypotheses

Based on our research question: *"What is the human attitude towards drone capabilities in contexts of different severity?"* we developed the following hypothesis:

- **H1:** The attitude of participants towards drone capabilities is more positive when the severity of the context is perceived as **high** compared to contexts with **low** perceived severity.
- **H2:** The attitude of participants towards drone capabilities is more positive when the severity of the context is perceived as **high** compared to contexts of **medium** perceived severity.
- **H3:** The attitude of participants towards drone capabilities is more positive when the severity of the context is perceived as **medium** compared to contexts with **low** perceived severity.
- **H4:** There is a **positive relationship** between the perceived **severity** of the context and the **attitude** of participants towards the drone capabilities.

4.2 Methodology

For each drone capability and context, we measured the subjective ratings of participants regarding their attitude towards drone capabilities in an online survey which was distributed through social networks and word-of-mouth. We furthermore hypothesize that the participants' attitude towards a capability is moderated by the severity of the context in which this capability could be applied. Based on prior work [13, 63], the perceived severity of harm, if no action is taken, is a motivational factor, for example to apply health-protective behavior or protective technologies. Thus, we expect the severity of context to have an influence on the attitude of participants towards drone capabilities. The type of drone capability and the type of context were manipulated within-subject resulting in a 10 x 6 repeated-measures design. This approach was chosen to control for individual differences in attitude ratings across participants and to increase statistical power.

4.2.1 Independent Variables. The study features two independent variables: **drone capability** and **context of use** based on the results of the PD study. Note that given the sheer amount of capabilities and contexts generated in the PD study, we had to run an additional study (pre-study) to finalize the process of selecting the independent variables.

Contexts of Use. We ran an online pre-study (N=18) with the goal to select 6 contexts of use that could be clustered into three severity levels – low, medium, and high. Based on the contexts elicited in the PD study (Table 2), and in agreement with members of the research team, we chose 15 contexts. Each participant (i.e., local students recruited via convenience sampling) received a link to an online questionnaire, read a description of the study, and signed an electronic consent form. They were then shown each context, presented as a text description, in a randomized order, and asked to rate the severity of the context on a 0-100 scale (from no harm at all to extremely devastating). We then checked for significant differences (p-values <.05) in severity between contexts using the Wilcoxon signed-rank test with p-values adjusted using Benjamini-Hochberg (BH) correction to control for False Discovery Rates (FDR). This helped us select two contexts of use for each severity level (low, medium, and high) with significant differences across severity levels and without significant difference within severity levels. This pre-study helped validate 6 contexts of use with 3 separate levels of severity (see Figures 1 and 3).

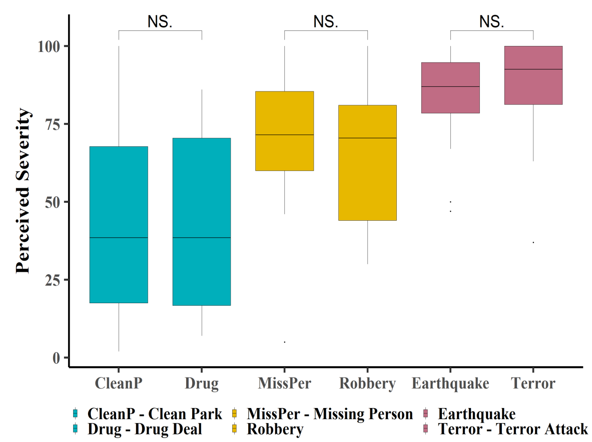

Figure 3: *Abbreviations.* Clean Park = A person is littering in a public park, Drug Deal = A drug deal is taking place on a street, Robbery = A person is robbing a store, Missing Person = A person is missing from home, Earthquake = An earthquake struck a city, Terror Attack = A stabbing is taking place at a bus stop. *Notes.* Visualization of the results as boxplots from the pre-Study (N=18) with the goal to select 6 contexts from a list of 15 contexts that can be clustered into three severity levels (low, medium, high). Contexts with low (blue), medium (yellow), and high (purple) perceived severity do not differ significantly within their severity group (e.g., severity rating of *Clean Park* does not differ significantly from severity rating of *Drug Deal*). However each context of a severity level differs significantly from all the others (e.g., *Clean Park* differs significantly from *Missing Person*, *Robbery*, *Earthquake*, and *Terror Attack*). p-values resulting from Wilcoxon signed-rank test were adjusted using Benjamini-Hochberg (BH) correction. NS = not significant.

Drone Capabilities. After we selected the 6 contexts of use, we consulted amongst members of the research team which 10 capabilities to test in the survey. Our decision was based upon discussions of which capabilities were the most applicable across all contexts of use. The 10 selected capabilities are presented in Table 3.

Table 3: Ten drone capabilities were tested in the attitude towards drone capabilities study based on the PD study. We used a subset of the capabilities to keep the online survey length appropriate.

Alerting	*Alerting the nearest police officer*
Detecting Gestures	*Detecting human gestures*
Detecting Humans	*Detecting human presence*
Detecting Objects	*Detecting specific objects*
Identifying Faces	*Identifying human faces*
Navigation	*Providing navigation*
Giving Feedback	*Giving auditory feedback*
Receiving Info	*Receiving auditory information*
Recording	*Recording (with video storage)*
Monitoring	*Monitoring (watch and keep track without storing video footage)*

4.2.2 Dependent Variables. The study includes two dependent variables: **the attitude towards drone capabilities** and **the severity of the context of use**. The first measure is the main variable of the study and the second is designed to verify that the severity was appropriately understood by the participants. The measurement for both variables is further detailed in subsection 4.2.5.

4.2.3 Participants. A total of 26 approved volunteers were sampled for the online survey (run on Qualtrics). Note that 4 participants who did not answer all control questions correctly were discarded from the original sample size (*N*=30). The participant pool was composed of 9 Female and 17 Male participants, 30.5 y.o. on average (*SD*: 8.3, range: 22–61 y.o.). The median duration of the survey was 26 minutes. At the end of the survey, participants could enter their email address if they wished to participate in the prize raffle, where two participants had a chance to win US$10.

4.2.4 Stimuli. We opted for video stimuli of the drone in context as such stimuli are widely used in Stated Preference (SP) experiments [53]. One advantage in using video stimuli over text explanations or images is that videos can increase the ecological validity of responses [49, 53]. The storyboards for the video clips were discussed and sketched with pen and paper within the research team. The storyboards were presented to and discussed with a group of HCI students and experts. Taking this feedback into consideration and conferring further with the research team, one of the authors designed the video clips for each of the 6 contexts of use, all presented through a cartoon art style (see Figure 1) using PowerPoint. The duration of the videos was between 12 and 21 seconds to ensure that the context is explicit and immediate. These videos do not show the actual drone capabilities in action, as to not bias participants in their answers. Yet, they display a given context in detail such that participants are provided with contextual information leaving little room for self-imagination while getting an understanding for the situation (e.g., city in an earthquake, a person littering in a park). Additionally, we used the same drone silhouette as in the PD study to not bias participants with any drone physical features.

4.2.5 Task Description. The online study consisted of two main tasks for each video stimulus to investigate the participants' attitude towards the drone capabilities in context, as well as the perceived severity of the context. As explained in the related work section, we opted for Taylor and Todd [59]'s 4-item Scale, which was also used in prior work [38]. This scale is based on one dimension and was reported in prior work to have a good reliability (λ^2 = .85). In Task 1, this scale was used to assess the participants' attitude [38, 59] towards the randomly listed drone capabilities for each given context (see Table 4). Note that in the questionnaire design, higher attitude scores correspond to a more positive attitude towards a capability (*feelings of favourableness*), whereas low attitude scores correspond to more a negative attitude towards a capability (*feelings of unfavourableness*). After each video clip, a control question followed to check whether participants correctly understood the context in the video clip. In the second task, the contexts were presented all at once in a randomized order. Participants were asked to rate the perceived severity of the context on a slider bar from 0 (no harm at all) to 100 (extremely devastating).

4.2.6 Procedure. Participants were first presented with the study description and asked to sign an electronic consent form. After reading the instructions, participants filled in a demographic questionnaire. The study proceeded to the first block of tasks where they performed Task 1 for each of the 6 video clips presented to them one-by-one in a random order. The second task followed thereafter. Participants were then thanked for their participation and asked if they wanted to provide their email address to participate in the lottery draw.

4.3 Data Analysis

As a first step of the data analysis, we generated the attitude scores of each participant by calculating the average of the 4 Likert-item values for each capability in each context (corresponding to 10 x 6 average attitude scores per participant). Following, we performed a Shapiro–Wilk test to check if the attitude scores within each capability and contexts are normally distributed. This was predominantly not the case, and as such we decided to use non-parametric statistical tests. To investigate whether the attitude scores of participants towards capabilities differed across the severity of contexts (see hypothesis: **H1**–**H3**), we performed a Wilcoxon signed-rank test. More specifically, we checked whether the attitude scores of participants towards a capability – corresponding to the average of the 4 Likert-item values, were significantly different for each combination of two contexts (e.g., attitude towards *Monitoring* for *Clean Park* (low severity) ≠ attitude towards *Monitoring* for *Terror Attack* (high severity)). Moreover, we tested whether there is a correlation between the perceived severity of context and the attitude scores of participants towards a capability (see hypothesis: **H4**) using Spearman's rho correlation (r_s). Note that the *p*-values resulting from the Wilcoxon signed-rank test and from the Spearman's rho correlation were adjusted using Benjamini-Hochberg (BH) correction to control for False Discovery Rates (FDR).

Table 4: Questionnaire answered by the participants to evaluate their attitude towards each drone capability in each context of use (i.e., for each video stimuli). Answers were obtained thanks to this 4-item questionnaire rated on seven-point Likert scales and adapted from [59].

Question	Lowest value (1)	Highest value (7)
Using the capability in the given situation is a(n) _____ idea	Extremely bad	Extremely good
Using the capability in the given situation is a(n) _____ idea	Extremely foolish	Extremely wise
I _____ the idea of using the capability in the given situation	Strongly dislike	Strongly like
Using the capability in the given situation would be _____	Extremely unpleasant	Extremely pleasant

4.4 Results

We here report the results of the study. Note that all statistical tests discussed as *demonstrating statistically significant results* have a p-value < .05.

4.4.1 Validation of severity in context. The validation of severity of context revealed that the low and high severity contexts from the pre-study were also found to be low and high severity within the online survey. We furthermore found that both medium severity level contexts differed significantly from both the low and high severity contexts as in the pre-study (see Figure 3). However, we found that, contrarily to the pre-study, there was a significant difference between the severity rating of the two medium severity level contexts: *Robbery* and *MissPer* (see Figure 4). For this reason, we separated these contexts into medium-low (*MissPer*) and medium-high (*Robbery*) for the rest of the data analysis. This resulted in 4 severity levels, namely: high, medium-high, medium-low, and low.

4.4.2 Human attitudes towards drone capabilities vs. severity. The results from comparing attitude scores for capabilities across severity levels (see Figure 5) revealed that participants' attitude across contexts was significantly higher[1] for **most capabilities** in:

- high severity contexts versus low severity contexts
- high severity contexts versus medium-low severity context
- medium-high context versus low severity contexts

Moreover, the attitude scores were significantly higher for **some capabilities** in:

- high severity contexts versus medium-high severity context
- medium-high context versus medium-low severity contexts

Importantly, we found that the human attitude towards capabilities was never significantly higher for low, medium-low, and medium-high severity contexts compared to high severity contexts. Moreover, the attitude was only higher for 2 capabilities (*Detecting Objects*, *Recording*) in the low severity contexts compared to the medium-low severity context, but besides these exceptions never higher for neither the medium-low severity context nor the medium-high severity context. This means that significantly higher attitude scores appear only (with 2 exceptions) for the contexts in which the severity was higher than the comparison group. We conclude that **H1**, **H2**, and **H3** were partially confirmed, meaning that the attitude of participants is more positive when the severity of the context is perceived higher.

[1]A significantly higher attitude towards a capability refers to a significantly higher *feeling of favourableness.*

4.4.3 Human attitudes towards drone capabilities in context. We found that the attitude of humans towards capabilities occasionally differed significantly within a severity level. This was the case for *Giving Feedback* in both low and high severity contexts, as well as *Detecting Humans* and *Navigating* in high severity contexts. Lastly, we found weak to moderate positive correlations (r_s = .20 − .44, p <.05) between perceived severity of context and attitude towards drone capabilities for each of the 10 capabilities (see Table 5 and Figure 6). To summarize, **H4** was fully confirmed, indicating that there is a positive relationship between the perceived severity of the context and the attitude of participants towards drone capabilities.

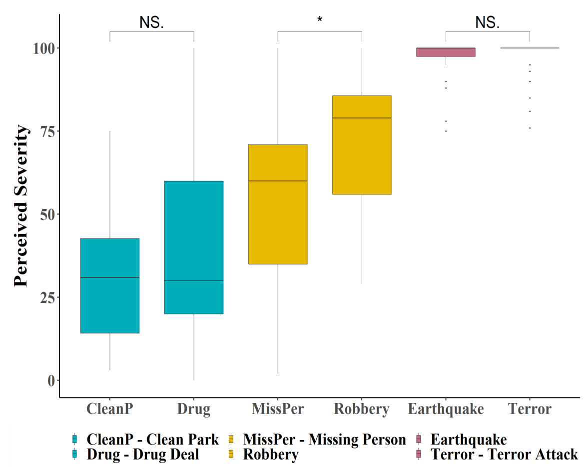

Figure 4: *Abbreviations.* Clean Park = A person is littering in a public park, Drug Deal = A drug deal is taking place on a street, Robbery = A person is robbing a store, Missing Person = A person is missing from home, Earthquake = An earthquake struck a city, Terror Attack=A stabbing is taking place at a bus stop. *Notes.* Visualization of the results as boxplots (N=26). Contexts with low (blue) and high (purple) perceived severity do not differ significantly within their severity group (e.g., severity rating of *Clean Park* does not differ significantly from severity rating of *Drug Deal*). However, other than in the pre-study, contexts with medium severity (yellow) differed from each other (*Robbery* was perceived as significantly more severe than *Missing Person*). Each context of a severity level differs significantly from all the others (e.g., *Clean Park* differs significantly from *Missing Person, Robbery, Earthquake* and *Terror Attack*). * indicates p-value<.05. NS=not significant.

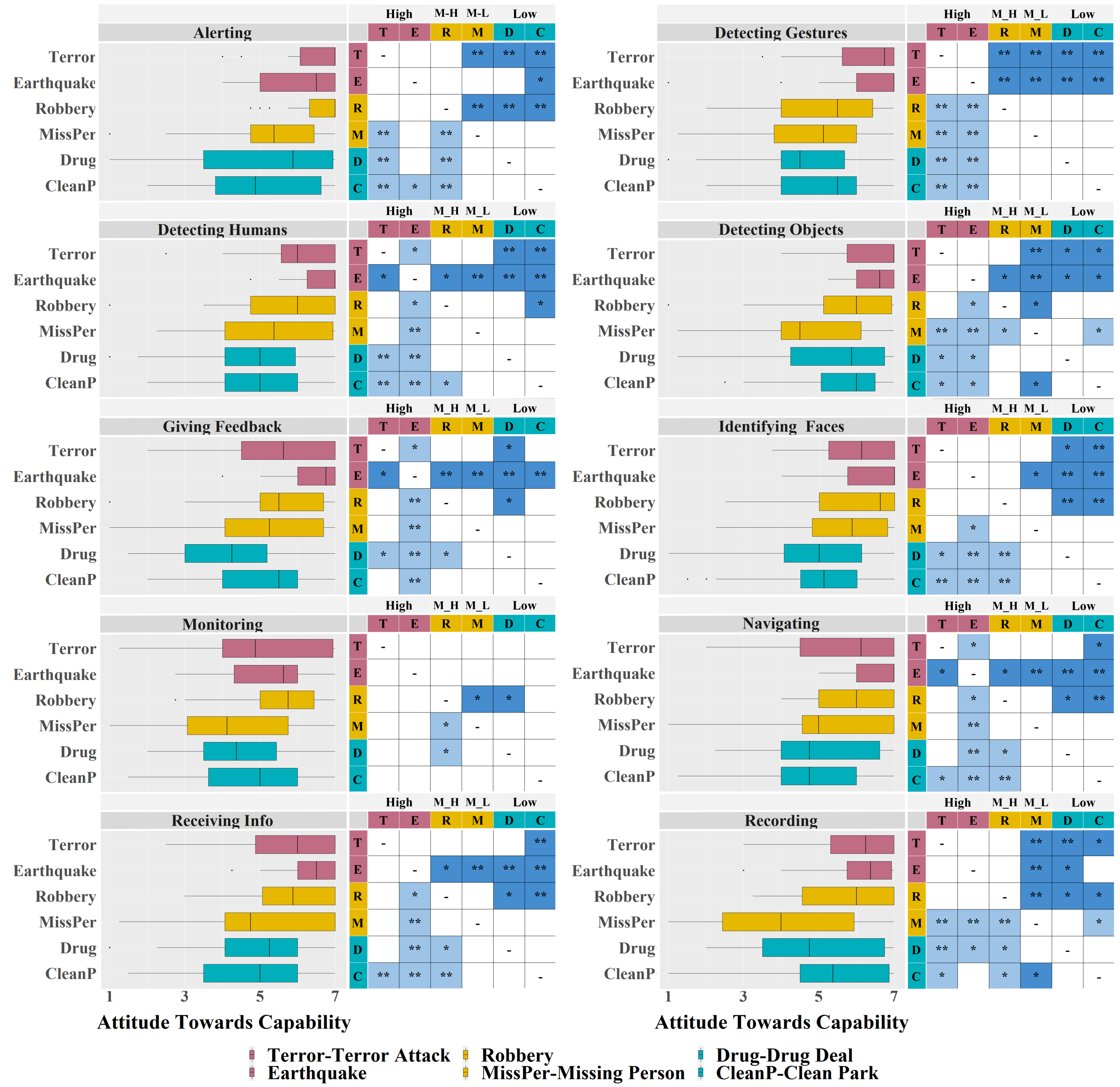

Figure 5: For each of the 10 drone capabilities a plot with 6 boxplots and a matrix is presented. The boxplots present the attitude ratings for each capability and each context. For example at the top left corner the attitude ratings for the capability *Alerting* (Alerting the nearest police officer) are presented. It can be seen that the attitude towards *Alerting* for the high severity context *Terror* is higher as for the low severity context *Clean Park*. Moreover each of the boxplot graphs has a matrix at the right side. This matrix indicates in dark blue for which contexts a capability was significantly rated with a more positive (higher) attitude. Thus it shows, for example, that the attitude for the capability *Alerting* was significantly higher for *Terror* compared to *Missing Person*, *Drug Deal* and *Clean Park*. Light blue indicates contexts in which the attitude towards a capability was significantly lower. Thus it shows for example that the attitude for the capability *Alerting* was significantly lower for *Missing Person* compared to *Terror*, and *Robbery*. *Abbreviations*: T = Terror Attack, E = Earthquake, R = Robbery, M = Missing Person, D = Drug Deal, C = Clean Park. p-values resulting from the Wilcoxon signed-rank test were adjusted using Benjamini-Hochberg (BH) correction. * indicates p-values <.05, and ** p-values <.01. The exact p-values can be found in Table A.1.

Table 5: Spearman's rho correlation coefficients (r_s) along with p-values for each of the 10 drone capabilities (see Figure 6). Note that the p-values resulting from Spearman's rho correlations were adjusted using Benjamini-Hochberg (BH) correction. All correlations were positive and significant (in bold) with coefficients ranging between r_s = .20 and r_s = .44.

	Alerting	Detecting Gesture	Detecting Humans	Detecting Objects	Giving Feedback
Spearman's rho r_s	**0.4**	**0.44**	**0.4**	**0.32**	**0.37**
p-value	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
	Identifying Faces	Monitoring	Navigating	Receiving Info	Recording
Spearman's rho r_s	**0.37**	**0.2**	**0.32**	**0.34**	**0.28**
p-value	<0.0001	0.015	<0.0001	<0.0001	0.0005

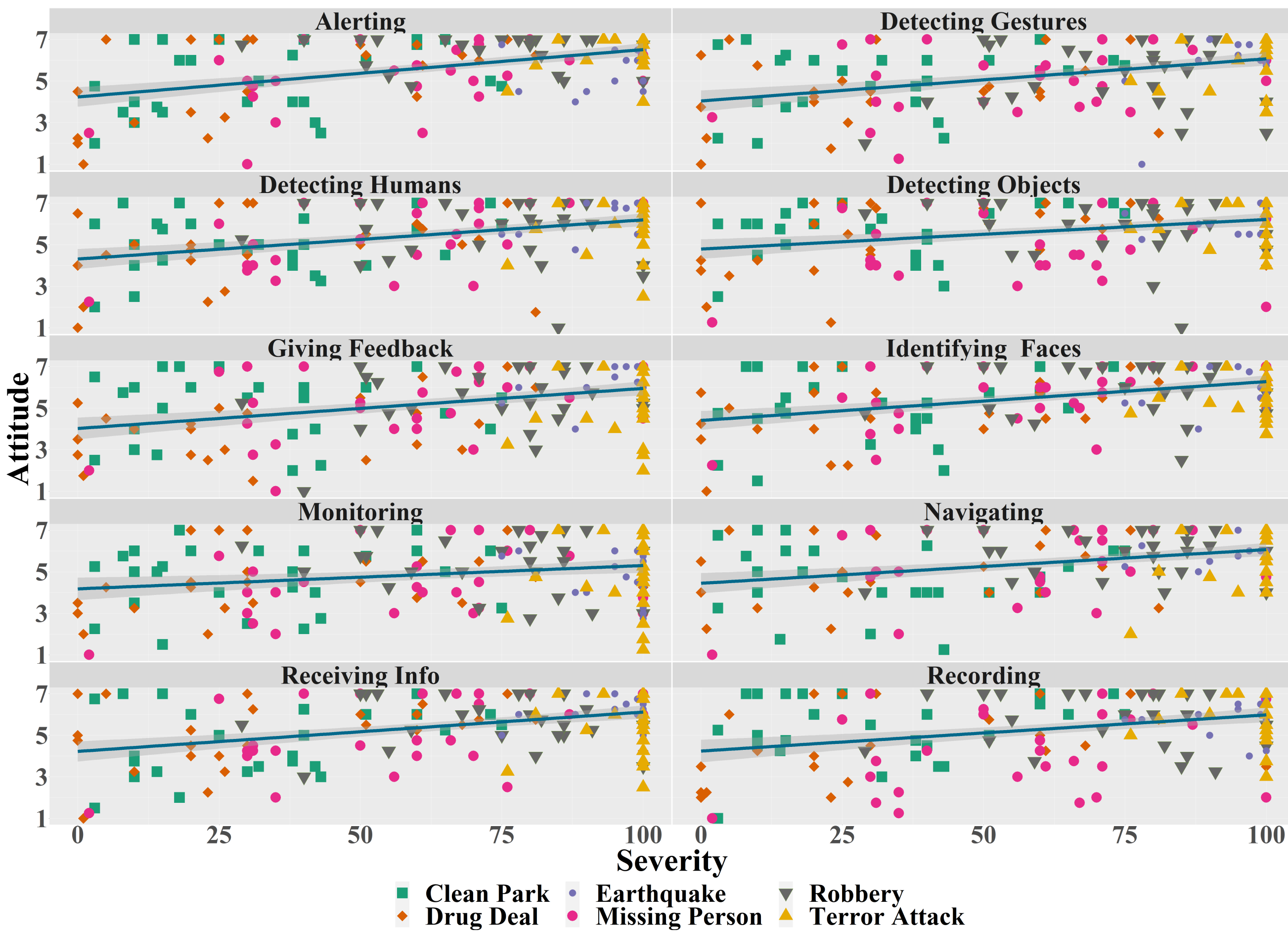

Figure 6: Spearman's rho correlations (r_s) between attitude ratings and perceived severity of context for each of the 10 drone capabilities. All correlations were positive and significant with coefficients ranging between r_s = .20 and r_s = .44 (see Table 5).

5 DISCUSSION

We discuss the potential offered by the insights gathered on human attitudes towards drone capabilities and how they are influenced by the severity of the context in which drones operate. We highlight particularly interesting aspects of human attitude towards drone capabilities in contexts of different severity levels. Moreover, we discuss the findings obtained in the PD study and more generally drones in law enforcement, and conclude with ethical implications.

5.1 People's Attitude, Severity of Context, and Capabilities

In this work, we hypothesized that people's attitude towards a set of drone capabilities is moderated by the severity of the context in which the capabilities could be applied. We proposed to focus on the perceived severity of context, as it was shown to influence behavioral intention to use protective technology [13], such as embodied by public drones. We verified our hypothesis and showed that, as the severity of context increases, people significantly become more favorable towards the proposed drone capabilities. Interestingly, we did not find, in average, negative attitudes towards any drone capability, and found that the majority of participants had a neutral to favorable attitude towards the full set of drone capabilities, regardless of the severity of context. In high severity contexts, we found that all drone capabilities are perceived favorably, even when they involve highly sensitive data collection and processing, such as recording with video storage and identifying faces. However, prior work showed that one of the main concerns expressed by people, regarding the use of drones in public spaces, is the loss of privacy [35]. Yet, our participants were neutral to favorable towards such capabilities in low severity contexts, and favorable in high severity contexts. This leads us to believe that the perceived benefits of a drone capability in a given context (e.g., help people or even save lives), could outweigh potential risks associated with the given capability. As such, barriers for the integration of drones in human spaces might decrease as people perceive the beneficial properties provided by public drones.

We further found that participants were more favorable towards two capabilities: detecting objects and recording, in a low severity context (*Clean Park*) over a medium-low context (*Missing Person*). We also found that for some drone capabilities: detecting humans; giving feedback; navigating, people's attitudes differed significantly *within* the two high severity contexts. These findings may indicate that people's attitude towards drone capabilities are not only influenced by the severity of context, but that additional factors could be considered. For example, in the PD study, a participant described the usefulness of drone capabilities over existing technology, such that a drone could leverage its flying abilities and be used for surveillance (i.e., recording) when someone is walking home at night, while a drone's surveillance of a parking lot seemed less useful given that the functionality can be fulfilled using a stationary camera. Similarly, in high severity contexts, one might think that a drone that provides navigation after an *Earthquake* is more useful than a drone that provides navigation during a *Terror Attack* (see Figure 5, navigating). Understanding these additional factors is primordial to ensure the acceptability of future public drones.

Finally, the predominant finding that people's attitude towards drone capabilities becomes significantly more favorable as the severity of context increases, leads us to believe that participants' chosen mental model embodies an 'end justifies the means' approach. This leads to ethical challenges that we further discuss below.

5.2 Ethical Implications and Challenges

In this section, we discuss some of the ethical challenges raised over the course of this work, and in particular in the PD study. One startling aspect of this work was how participants brought up the notion of weaponizing drones. Participants suggested, for example, public drones capable of using weapons in high severity contexts such as in terror attacks. While weaponized military drones already exist, current works looking at integrating drones in civilian spaces do not envision the use of weapons in public environments. In addition, prior work considered the ethical challenges of HRI design raised by automating policing with robots [5]. The paper described that deploying violent or lethal force in robots presents both legal and moral issues, and since a code of ethics has yet to be developed, we are not ready as societies to deploy such force in public robots and drones. Much research is needed on technological, legal, and societal aspects, to fully understand the implications of such capabilities in public drones.

Beyond the ethical challenges of using drones capable of using force against people or technologies, our work highlights additional ethical considerations. Some of these challenges were brought up in the PD study where participants stated: "*now you have eyes and ears everywhere*" and "*...record everything that is suspicious*". As part of this ethical consideration, we wonder whether the benefits of using public drones outweigh their drawbacks. The drawbacks and misuse of these technologies have led to widespread discussions in prior work. For example, while public drones can be used for property management, including surveillance around malls or monitoring of road traffic, challenges arise regarding data collection of individuals [67], which can create moral hazards for the public [64]. Choi-Fitzpatrick [14] emphasized the "need for a best-practices framework to guide" the use of public drones, and suggested following a set of principles, including: physical and material security, public interest, privacy, and data protection. Yet, there is a tension between the given principles, such as between individual privacy and public interest, exemplifying the remaining challenges of the usage of public drones. We further propose that robust regulations regarding public drones are needed, and according to West and Bowman [64], such regulations must be in favor of public safety, privacy, and accountability rather than expediency.

5.3 Capabilities and Visual Understanding

Beyond ethical challenges, the use of public drones includes other obstacles that need to be overcome, such as providing people with ways to understand and identify public drones and their capabilities. One major issue that arises from not understanding public drone capabilities is the increase of dangerous and dissatisfying interactions caused by a mismatch between people's expectations and the true capabilities of the drone [74]. To avoid such mismatch, prior work suggested making drone capabilities, such as recording, visually clear in order to decrease privacy concerns [62]. Moreover, it was shown that a drone's physical features affect how people perceive it on a series of dimensions [68], so that the presence of a camera on the drone leads to the drone being perceived as more intelligent. Based on these prior works and on our results, we propose that the design of public drones should be adapted to their capabilities.

In the PD study, participants used visual representations to describe some of the capabilities (e.g., using a camera for recording), while other capabilities were mentioned but not explicitly represented (e.g., alerting the police). A possible explanation is provided by prior work showing that visually conveying public robots' capabilities can be a challenging task [25], especially as some capabilities are easier to represent visually than others. As such, participants' drawings may be limited by their ability to draw specific capabilities (e.g., alerting the police) or to distinguish between features that correspond to multiple functionalities (e.g., a camera can be used to record, monitor, and identify faces). Future work should explore most appropriate designs for public drones considering their capabilities, abilities to interact [10], and their context of use.

6 LIMITATIONS

This work investigated the attitude of people towards drone capabilities in contexts clustered by different severity levels. Our study presents some limitations, such as in the use of video stimuli which do not induce the same level of emotion and realism that a person would experience in a real-life situation (e.g., earthquake). Yet, video stimuli are a helpful tool to investigate specific situations that are hard to investigate in real life – especially when the context is of high severity, yet this methodology is well accepted in prior drone research [26, 69]. Moreover, due to the low number of participants in the PD study (N=5), not all possible contexts and capabilities were gathered. We also acknowledge that the chosen contexts might be influenced towards first response and police drones and that additional applications are possible for public drones.

7 FUTURE WORK

Future work could investigate whether the attitude of people towards drone capabilities in varying contexts of severity, or their choices of visual designs, differ across cultures [20]. We found, for instance, that all participants chose red and blue colors to indicate police drones in their sketches, which could be due to cultural norms as all participants were from Israel. Moreover, future research should investigate whether one design of public drones is sufficient, or whether multiple designs are needed; as civil servants wear different uniforms to indicate different roles. Another insightful direction would be to investigate other facets of context, such as the number of people involved, time, and location. Additional work could explore situations where there is a mismatch between people's expectations and the actual capabilities of a public drone. Finally, future research could investigate the underlying mechanisms corresponding to why people tend to have a more positive attitude towards drone capabilities in high severity contexts compared to low severity contexts.

8 CONCLUSION

This work presented the first exploration of the influence of the severity of context on human attitude towards drone capabilities. We presented 3 user studies, one Participatory Design (PD) study, a pre-study, and a survey-based attitude study. As part of this work, we identified six contexts of use for drones in public spaces with different levels of severity. We then measured participants' attitude towards a range of ten drone capabilities in all contexts. We found that people's attitude towards all drone capabilities was significantly more favorable as the severity of context increased. We conclude with a discussion on people's attitude towards public drone capabilities, ethical implications and challenges, and acceptability of drones in public spaces. This work contributes to the growing field of human-drone interaction and to the design of context-sensitive drones and their future integration in human spaces.

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A APPENDIX

Table A.1: This table corresponds to the matrices presented in Figure 5 and provides the exact *p*-values when comparing each of the contexts within each capability. *p*-values resulting from Wilcoxon signed-rank test were adjusted using Benjamini-Hochberg (BH) correction. *p*-values are marked in bold for cases in which the Wilcoxon signed-rank test revealed significantly different ratings in attitude towards a capability (*p*-value <.05). Contexts marked in bold are significantly higher than the comparison context. Colors indicate the severity levels: low (blue), medium (yellow), and high (purple).

Capability	Context 1	Context 2	*p*-value		Capability	Context 1	Context 2	*p*-value
Alerting	Clean Park	Drug Deal	0.8689		IdenFaces	Clean Park	Drug Deal	0.9853
Alerting	Clean Park	MissPer	0.3038		IdenFaces	Clean Park	MissPer	0.0591
Alerting	Clean Park	**Robbery**	**0.0024**		IdenFaces	Clean Park	**Robbery**	**0.0053**
Alerting	Clean Park	**Earthquake**	**0.0219**		IdenFaces	Clean Park	**Earthquake**	**0.0053**
Alerting	Clean Park	**Terror**	**0.0025**		IdenFaces	Clean Park	**Terror**	**0.0058**
Alerting	Drug Deal	MissPer	0.7201		IdenFaces	Drug Deal	MissPer	0.2464
Alerting	Drug Deal	**Robbery**	**0.0038**		IdenFaces	Drug Deal	**Robbery**	**0.0054**
Alerting	Drug Deal	Earthquake	0.0722		IdenFaces	Drug Deal	**Earthquake**	**0.0024**
Alerting	Drug Deal	**Terror**	**0.0053**		IdenFaces	Drug Deal	**Terror**	**0.0219**
Alerting	MissPer	**Robbery**	**0.0026**		IdenFaces	MissPer	Robbery	0.1015
Alerting	MissPer	Earthquake	0.0591		IdenFaces	MissPer	**Earthquake**	**0.0120**
Alerting	MissPer	**Terror**	**0.0037**		IdenFaces	MissPer	Terror	0.0757
Alerting	Robbery	Earthquake	0.0948		IdenFaces	Robbery	Earthquake	0.2469
Alerting	Robbery	Terror	0.7160		IdenFaces	Robbery	Terror	0.9614
Alerting	Earthquake	Terror	0.1015		IdenFaces	Earthquake	Terror	0.1971
DetHuman	Clean Park	Drug Deal	0.5604		Monitoring	Clean Park	Drug Deal	0.6642
DetHuman	Clean Park	MissPer	0.2355		Monitoring	Clean Park	MissPer	0.5390
DetHuman	Clean Park	**Robbery**	**0.0370**		Monitoring	Clean Park	Robbery	0.0653
DetHuman	Clean Park	**Earthquake**	**0.0025**		Monitoring	Clean Park	Earthquake	0.1961
DetHuman	Clean Park	**Terror**	**0.0053**		Monitoring	Clean Park	Terror	0.3332
DetHuman	Drug Deal	MissPer	0.1173		Monitoring	Drug Deal	MissPer	1.0000
DetHuman	Drug Deal	Robbery	0.0609		Monitoring	Drug Deal	**Robbery**	**0.0336**
DetHuman	Drug Deal	**Earthquake**	**0.0024**		Monitoring	Drug Deal	Earthquake	0.0518
DetHuman	Drug Deal	**Terror**	**0.0058**		Monitoring	Drug Deal	Terror	0.2617
DetHuman	MissPer	Robbery	0.3769		Monitoring	MissPer	**Robbery**	**0.0285**
DetHuman	MissPer	**Earthquake**	**0.0045**		Monitoring	MissPer	Earthquake	0.0757
DetHuman	MissPer	Terror	0.2531		Monitoring	MissPer	Terror	0.4394
DetHuman	Robbery	**Earthquake**	**0.0123**		Monitoring	Robbery	Earthquake	0.6104
DetHuman	Robbery	Terror	0.3895		Monitoring	Robbery	Terror	0.2531
DetHuman	**Earthquake**	Terror	**0.0326**		Monitoring	Earthquake	Terror	0.4942
DetObject	Clean Park	Drug Deal	0.3038		Navigation	Clean Park	Drug Deal	0.3138
DetObject	**Clean Park**	MissPer	**0.0491**		Navigation	Clean Park	MissPer	0.1607
DetObject	Clean Park	Robbery	0.5289		Navigation	Clean Park	**Robbery**	**0.0030**
DetObject	Clean Park	**Earthquake**	**0.0302**		Navigation	Clean Park	**Earthquake**	**0.0024**
DetObject	Clean Park	**Terror**	**0.0151**		Navigation	Clean Park	**Terror**	**0.0147**
DetObject	Drug Deal	MissPer	0.2089		Navigation	Drug Deal	MissPer	0.5390
DetObject	Drug Deal	Robbery	0.2044		Navigation	Drug Deal	**Robbery**	**0.0180**
DetObject	Drug Deal	**Earthquake**	**0.0270**		Navigation	Drug Deal	**Earthquake**	**0.0025**
DetObject	Drug Deal	**Terror**	**0.0149**		Navigation	Drug Deal	Terror	0.1943
DetObject	MissPer	**Robbery**	**0.0128**		Navigation	MissPer	Robbery	0.1107
DetObject	MissPer	**Earthquake**	**0.0024**		Navigation	MissPer	**Earthquake**	**0.0053**
DetObject	MissPer	**Terror**	**0.0032**		Navigation	MissPer	Terror	0.3895
DetObject	Robbery	**Earthquake**	**0.0440**		Navigation	Robbery	**Earthquake**	**0.0232**
DetObject	Robbery	Terror	0.0887		Navigation	Robbery	Terror	0.4313
DetObject	Earthquake	Terror	0.5390		Navigation	**Earthquake**	Terror	**0.0128**
DetGestures	Clean Park	Drug Deal	0.1961		Receiving	Clean Park	Drug Deal	0.5520
DetGestures	Clean Park	MissPer	0.9853		Receiving	Clean Park	MissPer	0.4806
DetGestures	Clean Park	Robbery	0.2469		Receiving	Clean Park	**Robbery**	**0.0053**
DetGestures	Clean Park	**Earthquake**	**0.0025**		Receiving	Clean Park	**Earthquake**	**0.0024**
DetGestures	Clean Park	**Terror**	**0.0024**		Receiving	Clean Park	**Terror**	**0.0043**
DetGestures	Drug Deal	MissPer	0.3579		Receiving	Drug Deal	MissPer	0.9905
DetGestures	Drug Deal	Robbery	0.0757		Receiving	Drug Deal	**Robbery**	**0.0491**

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Capability	Context 1	Context 2	p-value
DetGestures	Drug Deal	**Earthquake**	**0.0025**
DetGestures	Drug Deal	**Terror**	**0.0024**
DetGestures	MissPer	Robbery	0.3148
DetGestures	MissPer	**Earthquake**	**0.0025**
DetGestures	MissPer	**Terror**	**0.0026**
DetGestures	Robbery	**Earthquake**	**0.0053**
DetGestures	Robbery	**Terror**	**0.0068**
DetGestures	Earthquake	Terror	0.5520
GivingFeedb	Clean Park	Drug Deal	0.0836
GivingFeedb	Clean Park	MissPer	0.9339
GivingFeedb	Clean Park	Robbery	0.2917
GivingFeedb	Clean Park	**Earthquake**	**0.0034**
GivingFeedb	Clean Park	Terror	0.3244
GivingFeedb	Drug Deal	MissPer	0.1224
GivingFeedb	Drug Deal	**Robbery**	**0.0133**
GivingFeedb	Drug Deal	**Earthquake**	**0.0024**
GivingFeedb	Drug Deal	**Terror**	**0.0326**
GivingFeedb	MissPer	Robbery	0.3138
GivingFeedb	MissPer	**Earthquake**	**0.0037**
GivingFeedb	MissPer	Terror	0.3138
GivingFeedb	Robbery	**Earthquake**	**0.0038**
GivingFeedb	Robbery	Terror	0.9614
GivingFeedb	**Earthquake**	Terror	**0.0385**

Capability	Context 1	Context 2	p-value
Receiving	Drug Deal	**Earthquake**	**0.0025**
Receiving	Drug Deal	Terror	0.0653
Receiving	MissPer	Robbery	0.1298
Receiving	MissPer	**Earthquake**	**0.0088**
Receiving	MissPer	Terror	0.0777
Receiving	Robbery	**Earthquake**	**0.0471**
Receiving	Robbery	Terror	0.9030
Receiving	Earthquake	Terror	0.1173
Recording	Clean Park	Drug Deal	0.1961
Recording	**Clean Park**	MissPer	**0.0135**
Recording	Clean Park	**Robbery**	**0.0237**
Recording	Clean Park	Earthquake	0.0748
Recording	Clean Park	**Terror**	**0.0166**
Recording	Drug Deal	MissPer	0.1152
Recording	Drug Deal	**Robbery**	**0.0156**
Recording	Drug Deal	**Earthquake**	**0.0229**
Recording	Drug Deal	**Terror**	**0.0053**
Recording	MissPer	**Robbery**	**0.0037**
Recording	MissPer	**Earthquake**	**0.0037**
Recording	MissPer	**Terror**	**0.0032**
Recording	Robbery	Earthquake	0.4108
Recording	Robbery	Terror	0.7201
Recording	Earthquake	Terror	0.6670

Concluded