Designing Drones: Factors and Characteristics Influencing the Perception of Flying Robots

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The last few years have seen a revolution in aerial robotics where personal drones are becoming pervasive to our environments and can be bought by anyone anywhere, including at local supermarkets. As they become ubiquitous to our lives, it is crucial to understand how they are perceived and understood by people. The robotics community has extensively theorized and quantified how robotic agents are perceived as social creatures and how this affects users and passersby. However, drones present different form factors that are yet to be systematically explored. This work aims to fill this gap by understanding people's perceptions of drones and how drones physical features correlate to a series of dimensions. We explored the quadcopters available on the 2018 market and built a dataset of 63 images that were evaluated in a user study (N=307). Using the study results, we present a model of how people understand drones based on their design and which physical features are better suited for people wanting to interact with drones. Our findings highlight that safety features have a negative effect on several dimensions including trust. Our work contributes a set of design guidelines for future personal drones and concludes on the implications for ubiquitous computing.

CCS Concepts: • **Human-centered computing → HCI design and evaluation methods**; **Ubiquitous and mobile computing design and evaluation methods**; *Interaction design*; • **Computer systems organization** → Robotics.

Additional Key Words and Phrases: Human-Drone Interaction, Human-Robot Interaction, Uncanny Valley, UAV, Anthropomorphism, Zoomorphism, Design, Amazon Mechanical Turk.

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1 INTRODUCTION

We are witnessing a new era of ubiquitous computing where robots and drones are becoming part of our lives beyond traditional personal devices. The number of consumer drones is expecting to reach 3.55 million units in the United States only, by 2021 [9]. These drones are being used for both leisure and professional activities, including photos and videos, search and rescue [21], agriculture, law enforcement, and surveying. With constant technological improvements, we envision new applications such as drones being used as tour guides [2, 10], sports coaches [42], and delivery services [61]. With progress in automation and artificial intelligence, we imagine

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drones will soon be assisting people in malls, at the grocery store, or even crossing a park safely at night [31]. Yet, to communicate with a drone in such situations, one must first understand the drone's intentions, its capabilities, and how to interact with it. To this purpose, collocated interactions with semi-autonomous drones need to be carefully designed and explored [66]. We foresee that increasingly, people will want to interact with a drone that is available or around them but that may not belong to them. As such, previous work argues for natural collocated human-drone interaction [6].

In addition to interaction capabilities, the drone in its design may convey some information regarding its intent, functions, and capabilities [35]. We find that in ground robotics, the design of the robot itself, its shape, size, color, and facial attributes influence how people perceive them [13, 18]. This is also suggested in Chang et al.'s work, who found that the color, size, and shape of a drone seem to influence how it is perceived [8]. Drones are different from ground robots in their ability to fly and how they are being designed. Prior work in HDI has shown that HRI findings on the ground robots do not directly apply to aerial robots [6, 26, 66]. We ponder how the prior research on designing ground robots can be applied to drones. What is the recipe to making a drone look friendly or trustworthy? Prior work shows that anthropomorphizing a machine, such as a vehicle [65], can positively affect people's trust towards the machine being capable of doing complex tasks. What are the characteristics that will help us design drones in the future to fit users' expectations? In particular, prior work has been focusing on the importance of the Uncanny Valley [37, 41] which hypothesizes that a person's reaction to a human-like robot will shift from empathy to repulsion as the robot's appearance looks increasingly human.

We propose in this work to identify and measure how a drone's physical characteristics affect how it is perceived. We also quantify which characteristics make a drone more prone to people wanting to interact with it. Our work contributions are as follows:

- A dataset of 63 drone images coded along 10 features;
- Empirical findings on how people perceive drones depending on their position on the machine-like to animal-like spectrum;
- Empirical findings on how individual design characteristics impact people's perception of a drone.
- Findings that current security measures are counteractive with regard to trust perception.

This paper first presents a literature survey of Human-Drone Interaction (HDI) and anthropomorphism design in robotics. We then describe our drone dataset, how it was built, coded, and evaluated. We then detail the results of a Mechanical Turk study (N=307) and present a set of design guidelines for future drone design. We further attempt to measure the drone uncanny valley and describe our preliminary results and directions for future work. We conclude with a discussion of our findings and implications for the ubiquitous computing community.

2 RELATED WORK

This section presents prior work on collocated human-drone interaction, anthropomorphism in human-robot interaction, how it is evaluated in the literature, and how it is applied to drones.

2.1 Human-Drone Interaction

Prior work on interaction with small-sized drones explored control mechanisms for collocated interactions, including voice [12, 47], gestures [6, 14, 26, 40, 43, 45], gaze [30], and touch [1]. Several feedback mechanisms have been proposed such as using LEDs to convey intent [60], a screen, a projector to display a map [2], or using the flight path to convey intent, affect, and emotions [7, 54, 59]. Affect and emotion have been specifically investigated as a first step towards integrating drones into humans' social environments. In their preliminary results, Arroyo et al. [3] show that different emotional states can be recognized and suggest that HDI can be improved if the drone conveys different emotional states. Cauchard, et al. [7] explored how a drone's emotions could be conveyed through different behaviors and flying paths. They showed that people can accurately associate emotional states to a drone. Recently, researchers have been working towards design guidelines for social drones that are suitable for interaction and companionship. Kim et al.'s ideal companion drone [32] presents "adorability" features. Yeh et al. [70] proposed a blue oval shaped drone and discussed how a tablet can be used to display a "friendly face". Karjalainen et. al. [29] investigated several features and found that emotional characteristics were desirable, and they also suggest that the drone appearance should be a round shape with a face. The above literature shows that physical design and behavior is a central aspect of designing social drones intended to interact with people.

2.2 Designing for Anthropomorphism

Anthropomorphic design has previously been defined as "a tendency to attribute human characteristics to inanimate objects, animals and others with a view to helping us rationalize their actions" [13]. Złotowski et al. [73] present a survey paper reviewing why people anthropomorphize robots. We find that anthropomorphism plays an essential role in how people perceive socially interactive robots and interact with them [18]. It also helps generate trust between people and service robots [56, 72] or vehicles [65]. The Uncanny Valley theory [41] advances that when a robot appears too similar to a human, it appears less familiar to people. Designers are warned that the look of a machine should match its capabilities and as such users' expectations [18, 55]. Anthropomorphism is a function of the robot's appearance, behavior, and interaction [19]. In terms of the robot's appearance, prior research investigated specific features including: robots' bodies [46], faces [27], heads [11, 23], skin [46], and even hair [15]. Research showed that gender [16, 44, 46, 52, 56], culture [28], and context play a role on how a robot is perceived. Yet, not all machines are anthropomorphized in the same way [73], the following section discusses how anthropomorphism is evaluated in the literature.

2.3 Evaluating Anthropomorphism

Different methodologies have been used to evaluate anthropomorphism and how robots are perceived. Wang et al. [64] surveyed studies specifically investigating the Uncanny Valley phenomenon. In terms of methodologies, user studies have been conducted where participants were shown robots as pictures [11, 20, 49] or videos [35, 36] in person, or online using tools such as Mechanical Turks [27, 38, 48]. Live trials with a robot [63, 74, 75] have also been conducted. Woods et al. [68, 69] show that the live trial methodology and video-based approach share a high degree of agreement. In these studies, a spectrum of dimensions were investigated, such as: likeability, trust, interaction, emotionality, familiarity, perceived dangerousness, uncanniness, and intelligence. Participants' feedback was received through questionnaires and surveys [5], some used gaze behaviors [39], and more invasive approaches have been proposed, such as functional magnetic resonance imaging (fMRI) [51].

2.4 Drones and Anthropomorphism

A large body of work investigated humanoid robots and robotic faces, which are different from today's drones. When characterizing drones, we find that most of the literature mentions, although as anecdotes, the drone being considered or referred to as an animal or a pet [1, 6, 7, 14, 17, 32, 43, 50]. Although surprising because of their non-anthropomorphic nature, this is in line with prior work that showed that low or non-anthropomorphic robots still get anthropomorphized [57], usually "focusing on body movements, gaze and other nonverbal behaviors" [71]. In a comparative study, Austermann et al. [4] found that people seemed to prefer a pet-shaped robot to a humanoid. While this concept can be referred to as zoomorphism, it can be impossible to know whether people are actually anthropomorphizing or zoomorphizing a machine when referring to features that are present in both humans and animals such as "eyes". As such, we will exclusively use the term anthropomorphism in this paper. To the best of our knowledge, drones have not yet been researched in terms of anthropomorphism and it is not known whether different designs would lead to different perceptions from people. In the next section, we present our method for investigating this research question.

3 METHOD

Our proposed method is derived from Mathur and Reichling [38] and Kalegina et al. [27] studies on robot faces characterizations using Mechanical Turk. This section describes our method, including the selection of the drone images, the identification of drones' physical features, questionnaire design and dimensions of perception, and the Mechanical Turk study.

3.1 Drone Images Dataset

For this first investigation, the scope of this work was limited to existing consumer products, which are designed and built under real-world constraints for the purpose of being sold. We focused on quadcopters as there are the most popular type of consumer drones. The dataset was built using drone images collected by web search. The keywords included but were not restricted to: "drone", "UAV", and "quadcopter", and adding qualifiers such as: "animal", "cute", "with eyes". The search was conducted in multiple languages including: Chinese, English, French, Japanese, Korean, and Spanish. Web search was performed over the course of a month prior to the study to ensure all possible drones on the 2018 market were identified. All drones were considered regardless of their popularity or market availability. Inclusion and exclusion criteria were defined, so that the dataset would be composed of comparable images.

Inclusion Criteria:

- The drone is a quadcopter (i.e., has four propellers).
- The drone is at rest (i.e., its propellers are not moving).
- The drone is shown in frontal to 3/4 aspect.

Exclusion Criteria:

- The drone represents a well-known movie character (e.g., Weebo in Flubber [34]).
- The image includes other objects or text.
- The image includes recognizable stickers or logo.
- The image quality in under 500x500 pixels.

We found 102 qualifying images, that were then checked for pairs with high similarities. When two images were sufficiently similar, only one was kept, which resulted in a total of 63 drone images selected for the final set[1]. Each remaining image was then harmonized to the dataset. Images were cropped and/or reduced in size to fit in a 500x500 pixels square. When the background was not white or off-white, a white background was applied. We kept two images for which a white background could not be applied as they showed unique features that we wanted to study. Figure 1 shows the final dataset [2]. This research is based on Mathur and Reichling [38] and Kalegina et al.[27] studies which use static images. Designing a video dataset would have required buying every drone available on the international market to make the videos, or finding consistent videos of each and every drone, which do not exist. Static images are nonetheless the most commonly available source of information when a customer buys a drone in store or online.

[1]Many drones presented highly similar features, and we suspect that a few drone manufacturers sell the same model to companies who then perform light customization.
[2]Note that the images included in this paper are under ACM guidelines on Fair Use.

Fig. 1. Generated dataset of 63 drone pictures. The images are displayed in descending order of animal-likeness, from the most animal-like (#1 - top left) to the most machine-like (#63 - bottom right), in the Mechanical Turk study.

3.2 Drone Physical Features

To identify how the appearance of a drone affects how it is being perceived, 10 physical features were chosen based on the literature presented in 2.2, the dataset itself, and discussions among the research team. Three features are related to facial features, two define accessories, two are based on colors, two on the drone's shape, and one on whether it was designed to look like an animal. The list of features is as follows:

- **Eyes**: The drone presents some elements in its shape, color, or design that can be understood as two eyes on the front part of the drone.
- **Mouth**: The drone presents some elements in its shape, color, or design that resembles the shape of a mouth, snout or beak.
- **Facial features:** The drone presents at least one feature that can be recognized as facial feature.
- **Guards**: A safety hull (or propeller guards) is present around the propellers.
- **Camera**: A camera is visible on the drone.
- **Drone color**: The drone's body is over 50% black & white (Grayscale) or over 50% color (Colorful).
- **Eye color**: When eyes are identified, the color is determined as: Dark (black or grey) or Color. Note: eyes can be made of different materials and have different brightness levels.
- **Body shapes** If the drone presents curvy lines on its body or around the propellers or guards, it is considered Curvy; otherwise Straight.
- **Rounded**: The drone's body presents a circular or round shape, regardless of the propellers' shape and position.
- **Animal Representation:** The shape, form, or design was inspired by an animal.

Two researchers encoded the dataset separately. They then checked where the encoding concurred, and a third member of the research team weighed in when the findings differed. Agreement between the two researchers was 99.8%; Cohen's Kappa, measure of inter-rater reliability, was 0.986 ($z=24.7$, $p < 0.001$).

3.3 Questionnaire Design & Dimensions of Perception

For each image, a questionnaire was administered, it presented six 100-point semantic differential scales and two continuous rating scales of 0 to 100. Each scale corresponds to a dimension of perception to establish the design space for human-drone interaction. The chosen dimensions are based off prior work and adjusted to this study such that when prior work looked at machine vs. human-likeness [27], we studied machine vs. animal-likeness.

The questionnaire investigates the following 8 dimensions:

- *Animal Likeness*: Machine-like 0 – Animal-like 100
- *Friendliness*: Unfriendly 0 – Friendly 100
- *Intelligence*: Unintelligent 0 – Intelligent 100
- *Trustworthiness*: Untrustworthy 0 – Trustworthy 100
- *Age*: Childlike 0 – Mature 100
- *Gender*: Masculine 0 – Feminine 100
- *Interaction*: "How much would you like to interact with this drone?"
- *Likeability*: "How much do you like this drone?"

There was a final compulsory open question for each drone regarding its perceived functionality: "What do you think this drone can do?" The order of images was randomized for each subject and the subjects controlled how long they viewed each image with no time limit.

3.4 Mechanical Turk

The survey was distributed via Amazon Mechanical Turk (mTurk), a crowdsourcing platform allowing workers, over 18 y.o., to complete online tasks for pay. The mTurk workers were sampled with an excellent performance history, HIT approval rate ≥ 97, and an approved number of HITs ≥ 100. Participants were asked to read and sign an anonymized electronic consent form, answer demographic questions related to age, gender, level of education, and country of residence. They were then presented with 31 randomized drone images and questionnaires. Half way through the study, participants were asked to answer a simple control question to check their attention span. We disqualified two surveys for which the control question was incorrect or for which the exact same answer was given to all questions. At the end of the survey, participants answered additional questions about previous experience with drones.

A total of 307 approved volunteers[3] were sampled for this study. The participant pool was composed of 131 female, 174 male, and 2 non-binary gender participants, between the ages of 20 and 74 y.o. (μ = 37.8, SD = 10.8). Participants were distributed at 79% in North America, 18% Asia, 3% from Europe and South America. 75% of participants had a college education or higher, and the large majority (92%) reported having seen a drone prior to participating in the study. On average, questionnaires were completed in 33min 13sec, and drone images rated in 1min 4sec. Workers were paid based on the U.S federal minimum wage of US$7.25 per hour [22]. We offered bonuses ranging from $0.50 to $1.00 to Turkers who, judging by their questionnaire responses, put extra effort into their work, such as elaborating on the open questions.

4 RESULTS

This section first discusses how each dimension has been rated, then presents the correlations amongst dimensions, and finally the linear regressions between dimensions and features.

4.1 Dimensions of Drone Images

This section presents the results according to each one of the 8 dimensions described in 3.3 *Questionnaire Design*. Individual drone values are calculated as medians of the 100+ individual answers. For discussion purposes, a value is considered at the lower or higher end of the spectrum if it is <30 or >70 on the scale.

(a) Intelligent

(b) Mature

(c) Interaction

(d) Likeability

Fig. 2. Drones rated as the most: intelligent (a), mature (b), desired for interaction (c), and preferred overall (d).

[3]We requested 300 responses and received 309 completed surveys, which resulted in some drones getting a few more than 100 answers.

4.1.1 Animal-likeness. We found a wide distribution in the animal-likeness dimension from 6 to 94. The large majority of drones (89%) were rated on the machine-like side. Interestingly, most of the remaining drones were perceived at the higher end of animal-like, while the machine-like drones varied on the spectrum. Anecdotally, these drones had clear animal characteristics such as, designed to look like a dog, a dove, or a ladybug, including facial features. Figure 1 shows the classification of the drone images dataset from the most animal-like (#1) to the most machine-like (#63).

4.1.2 Friendliness. Drones were mostly considered as friendly (70%) and few of them very friendly. Among the unfriendly drones, none were perceived as strongly unfriendly (lower end). The four most friendly drones are also the four most animal-like (Figure 1 - drones #1,#2,#3, #4).

4.1.3 Intelligence. The large majority (95%) of drones were rated on the intelligent side of the scale. 19% were on the higher end and only one below the mid-point line. Figure 2a shows the four most intelligent drones.

4.1.4 Trustworthiness. All drones were on the trustworthy side, with three on the higher end of trust. Interestingly, these drones are also the three most animal-like drones (Figure 1 - drones #1,#2,#3).

4.1.5 Age. We see a large diversity with most drones (79%) being considered Mature, including 24% at the higher end. Only three drones were rated at the lower end of child-like, and correspond to three out of the four most animal-like drones (Figure 1). The four most mature drones are shown in Figure 2b, two of them correspond to the most intelligent drones.

4.1.6 Gender. Most drones (67%) were rated as masculine, 25% as feminine, and 8% were on the mid-point line. The two most masculine drones are the same as the two most intelligent and mature drones (Figure 2b), whereas the three most feminine drones are a subset of the four more animal-like drones (Figure 1 - drones #2,#3,#4).

4.1.7 Interaction. All drones passed the mid-point, with only few drones with a neutral score, and most (95%) at a favorable interaction score. Only four drones were rated at the higher end of interaction (Figure 2c).

4.1.8 Overall Preference. Most drones (94%) were rated above the mid-point in likeability, with a few drones at the higher end. Only three drones were rated under the mid-point but close to it. Preferred drones are shown in Figure 2d.

This next section describes the correlations between dimensions. In Section 4.4, the dimensions are discussed one more time in comparison with the drone physical features.

4.2 Dimensions Correlations

A Pearson's correlation was run to investigate the relationship between the dimensions of perception for all 63 drone images.
Table 1 shows the Pearson product-moment correlation coefficients r with confidence intervals: $p < 0.05$ (*) and $p < 0.01$ (**). Given the large number of significant correlations, we summarize below the moderate, high, and very high correlation sizes [25].

- **Animal-likeness:** Moderate correlation with friendliness, child-likeness, and feminine.
- **Friendliness:** Friendliness significantly correlates with all other dimensions. High correlation with trustworthiness, child-likeness, and feminine. Moderate correlation with interaction and likeability.
- **Intelligence:** High correlation with maturity. Moderate correlation with likeability.
- **Trustworthiness:** High correlation with interaction. Moderate correlation with feminine and likeability.
- **Age:** High correlation between child-like and feminine.
- **Interaction and Likeability:** Very high positive correlation, almost linear, between interaction and likeability.

Table 1. Table of Pearson's correlations between pairs of dimensions from the Mechanical Turk questionnaire. Each block shows Pearson's r(63)'s value with ** ($p < 0.01$) and * ($p < 0.05$).

	Machine - Animal	Unfriendly - Friendly	Unintelligent - Intelligent	Untrustworthy - Trustworthy	Childlike - Mature	Masculine - Feminine	Interaction	Likeability
Machine - Animal		.636**		.463**	-.669**	.620**	.249*	.248*
Unfriendly - Friendly			-.357**	.886**	-.773**	.834**	.575**	.526**
Unintelligent - Intelligent					.761**	-.490**	.454**	.503**
Untrustworthy - Trustworthy					-.494**	.658**	.739**	.687**
Childlike - Mature						-.819**		
Masculine - Feminine							.288*	
Interaction								.981**
Likeability								

Table 2. Drone features best modeling dimensions to predict the 8 proposed dimensions according to the results of the Mechanical Turk study, with ** ($p < 0.01$) and * ($p < 0.05$). Features with empty cells were not kept in the corresponding regression model.

	Intercept	Guards	Eyes dark	Eyes color	Mouth	Camera	Curvy	Colorful	AIC
Machine - Animal	30.2**	-	14.1**	4.8	5.9	-9.3**	6.2	13**	476.5
Unfriendly - Friendly	44.1**	-5.3*	8.2**	0.8	-	-	10.2**	7.5*	453.6
Unintelligent - Intelligent	56.4**	-	4.2*	7.2**	-2.9	7.6**	-	-3.6	403.8
Untrustworthy - Trustworthy	54.8**	-2.3	-	-	3.1*	-	3.1	3.7*	384.1
Childlike - Mature	65.9**	-	-	-	-7.9**	9.7**	-9.8**	-13.8**	465.5
Masculine - Feminine	37.2**	-	3.2	-4.1	5.4	-5.3*	8.1**	9.1**	441.1
Interaction	49.6**	-1.7	3.4*	3.4*	-	3.7**	4*	-	368.3
Likeability	49.6**	-1.9	3.6*	4.5**	-	4.2**	3.9*	2.1	380.3

4.3 Impact of Drone Physical Features

We used stepwise regressions with Akaike information criterion (AIC) optimization to model the relationships between each dimension and drone features. As compared to other criteria, AIC is best suited to find a model that is robust to new data [33]. A stepwise regression works by incorporating factors one by one, using AIC to estimate and compare the models. Only factors that increase the model's robustness are kept. To obtain linear models that include at least 10 drones per category, some features had to be merged. Note that due to the important number of factors and to avoid combinatorial explosion we did not include interaction effects in our models. Table 2 shows the first model for designing drones according to dimensions and features. The cell values correspond to the regression values, empty cells denote factors that were not kept in the regression models.

In the final regression analyses, features were coded as follows:

- Eyes: none (N=33), Dark (N=17), Color (N=13)
- Mouth: without (N=44), with (N=19)
- Guards: without (N=39), with (N=14)
- Camera: without (N=24), with (N=39)
- Color: Grayscale (N=52), Colorful (N=11)
- Body shape: Straight (N=10), Curvy (N=53)

To interpret these results for the design of future drones, let us consider the following example using the gender dimension, which scores can be predicted, following the model's features:

$$Gender = 37.2 + 3.2\text{ (dark eyes) or } -4.1\text{ (colored eyes) } +5.4\text{ (mouth) } -5.3\text{ (camera) } +8.1\text{ (curvy) } +9.1\text{ (color).}$$

As such, the most "feminine" drone has dark eyes, a mouth, curvy lines, and colors; and the most "masculine" has colored eyes and a camera. Comparing regressions values across all dimensions, we rank drones' features by decreasing order of importance: color, shape, camera, eyes and eyes color, mouth, and propeller guards.

We below discuss how each feature affects the various dimensions and the opposite.

- **Propeller Guards:** The safety hull surrounding drones' propellers resulted in the drones being rated less friendly, less trustworthy, less likely to interact with, and less likeable.
- **Eyes:** Drones with eyes were perceived as more animal-like, friendly, and intelligent. Interestingly, the eye color influences the perceived gender of the drones. Overall, the presence of eyes increased interaction and likeability scores.
- **Mouth:** Drones with mouth, snout, or beak features were rated more animal-like, trustworthy, feminine, less intelligent, and more mature.
- **Curvy lines:** A majority of drones present curvy lines on their body or around their propeller guards. These drones were rated more animal-like, friendly, trustworthy, child-like, and feminine. People also tended to like them more and wanted to interact with them more.
- **Color:** Colorful drones were perceived more animal-like, friendly, trustworthy, feminine, and likeable. Grayscale drones were ranked as more intelligent and more mature.
- **Camera:** Drones with a visible camera were perceived more machine-like, intelligent, mature, and masculine. They also presented a higher score on interaction and likeability.

4.4 Dimensions vs. Drone Physical Features

Below we detail how the drone features from the models defined in the previous section influence each dimension.

- **Animal-likeness:** Drones are more animal-like with facial features, curvy lines and colors, and when they do not exhibit a camera.

- **Friendliness:** Friendly drones have eyes, a curvy and colorful body, and do not feature propeller guards.
- **Intelligence:** Grayscale drones with eyes and camera but without mouth are perceived more intelligent.
- **Trustworthiness:** Drones that feature a mouth and a curvy and colorful shape are perceived more trustworthy. Drones with propeller guards are ranked as less trustworthy than the ones without.
- **Age:** Childlike drones have a mouth, curvy lines, colors, but no visible camera.
- **Gender:** Feminine drones have facial features, as well as curvy lines and are colorful. Masculine drones have less facial features, colorful-eyes, straight lines, a visible camera, and are black & white.
- **Interaction:** Overall, people would be more likely to interact with drones that feature eyes, a visible camera, and curvy lines. People would be less likely to interact with drones that have propeller guards.
- **Likeability:** As per interaction, drones with eyes, a visible camera, curvy lines, and without propellers guards were preferred. The only notable difference between Interaction and Likeability was the drone color, which positively influenced likeability.

4.5 Capabilities

This section discusses the results of the open-ended question on the drone capabilities. Some answers were well detailed. We classified the answers in three categories: related to applications, characteristics, and abilities.

4.5.1 Applications. Many existing applications were mentioned, such as drone delivery, photography, video, search and rescue, agriculture, research and science, surveillance, and other military applications. Participants also introduced unexpected novel applications such as swimming and landing on water, playing games with people or pets, being used as a companion, broadcasting, gardening, as a medical drone for wildlife, and also drones for education.

"This drone might offer life saving assistance"	P129
"This drone can be used to predict weather forecasts and send warnings"	P36
"a medical type of drone [...] and give shots or some sort of medicine to help heal animals that are dangerous"	P248

4.5.2 Characteristics. Drones were often anthropomorphized with arms, legs, and facial features, including eyes and mouth. They were compared to animals and pets, including insects, such as butterflies and spiders. They were given personality traits, being: "friendly", "scary", and "trustworthy". Their shape would sometimes determine their job, such as a drink delivery drone which is "flat". There were comments on quality: "sleek", "sturdy", "flimsy"; and also on cost, cheap or expensive. Participants found size-attributes for the drones: "tiny", "small", "big", despite all drones being shown at the same size without any reference point. Weight and materials were also discussed.

"it looks like a raft, like it would float in the water"	P201
"This is a clumsy drone - it works with younger children and in elementary schools.	P195

4.5.3 Abilities. Drones were attributed special skills. Some were movement-related such as: rolling, climbing, swimming, and of course flying. Drones were also described as: fast, slow, and capable of flying short or long distances, and high altitudes. Participants also attributed interaction capabilities such as speech to the drones. Unusual skills included flying in dangerous places, night vision, flashing light, playing audio, and air acrobatics. Participants also discussed levels of automation.

"could be used in very tight, closed spaces"	P301
"It can probably do aerial acrobatics like loops and flips."	P212
"The race car like colors and the sleek design make it look like this would be a very fast drone"	P95

The next section discusses how these results can be used to generate design guidelines for future drones.

5 DESIGN GUIDELINES

As the drone market expands, we envision drones will be built and designed for specific applications and usage scenarios. The results of our study inform future drone designs by selecting the appropriate physical features to elicit a particular response. We present three examples of future drones, and how we use our model to build new drones. Several options and designs are possible, and the following are used for illustrative purpose. We emphasize that these serve as guidelines based on people's perception of drones as per our study.

5.1 Delivery Drone

We first determine the dimensions required for a delivery drone. We agreed it needs to be trustworthy, so people will trust it with their deliveries or handing it money; and likeable, to be pleasant and sociable, as when representing a small business owner. We found a moderate positive correlation between trustworthy and likeability (Table 1), dimensions which share common features in our model (Table 2). The model predicts that to elicit these particular responses, this delivery drone should have facial features, such as eyes and mouth, a curvy and colorful form, and no propeller guards.

5.2 Toy Drone

A toy drone may be more complex to design. We propose that it should have the following dimensions:

- *Animal-likeness:* Happiness was associated with a human-like or animal-like appearance in prior work [67].
- *Friendly and Likeable:* It is a toy!
- *Childlike:* Relatable to the child.
- *High Interaction:* For the child to want to play with it.
- *Feminine:* Since male robots were associated with negative emotions and behavioral intentions in prior work [67].

Our results suggest that animal-like drones tend to be designed to clearly resemble an animal including facial features (4.1.1). Animal-like correlates to friendly, child-like, feminine, and interaction. According to the model, and to elicit these responses, the toy drone should present curvy lines and colorful features, which increase scores across all five dimensions; and no camera or propeller guards that are detrimental to most dimensions[4].

5.3 Science Drone

We first determine the dimensions needed for a science drone. We identified that it needs to be intelligent, mature and trustworthy, so people will be able to trust and depend on it with getting the relevant information. We also identified the need for interaction as the drone might become part of the research team [62]. Intelligence is correlated with interaction, and trustworthiness. Our study shows that intelligent and mature drones have grayscale colors, have technical gear such as a camera, and should not have a mouth. Results also suggest that to

[4]Note that we recommend that safety features be present on toy drones. This corresponds to people's perception and not actual safety considerations.

be recognized as mature, a drone should have straight lines. Science drones should balance those features with eyes and an absence of propellers guards to increase trust and the desire to interact with them.

6 DISCUSSION

This section discusses the lessons learned during our study.

6.1 Drone Design

This work provides empirical evidence that the integration of physical features in drone design affects how this technology is being perceived and understood by people. These findings are critical at a time when people make drone purchasing decisions based on images. We contribute a model of physical features and show how they affect drones' perception across eight dimensions. We found that the presence of facial features has an effect on every single dimension of perception. For instance, to appear more intelligent a drone needs eyes but no mouth. Also, we found that the presence of a mouth increases interaction and likeability. Color and shape have an input on all but one dimension. For example, curvy and colorful drones are perceived as more friendly and childlike. We found that drones with clear animal features, such as a dog or a dove, had a strong impact on how they were rated and stood out compare to other drones. Prior literature suggested a social drone to have a blue oval shape with a face [70] or a round-shape with facial features [29]. Chang et al. [8] proposed designing "friendly" drones with colors and suggested using a circular drone shape. Our results corroborate these findings, as our model shows that a drone is most friendly when designed with colors, curvy lines, and black eyes. However, while prior work suggested that social drones should include propeller guards [29], our findings highlight that propeller guards have a negative correlation on all social dimensions – namely friendly, trustworthy, interaction, and likeability.

6.2 Safety and Perceived Trust

Our results highlight that propeller guards have a negative effect on friendliness, likeability, interaction, and trust, and no positive effect on any other dimension. This is worrying as propeller guards are currently the main safety mechanism in drone design and are crucial to create safe interaction between people and drones. We observed that most animal-like drones, which were often referred to as toys, do not have any visible safety mechanisms. We found that drones with safe enclosed propellers appear at the end of the machine-like spectrum. Prior work has mentioned study participants wanting to touch or pet a drone [6]. This shows the high discrepancy between the potential danger of drones with opened rotating blades, and how people actually perceive them. We argue that additional research is needed to fully understand how to design safe drones that people will be comfortable interacting with. We emphasize that we do not recommend fully removing the propeller guards, rather researching and re-designing safety mechanisms that can increase the sense of trust and the willingness to interact with a drone.

6.3 Anthropomorphization

While most drones are designed in a non-anthropomorphic manner, participants attributed body-like features to the drones as well as emotions and personality traits. This is in par with prior work where people conducted in person studies with drones [7, 54] and comparable to prior work in ground robotics [58]. This finding is interesting as participants are only shown images and do not get to experience how drones move or what type of noise is being generated. Drones were given gender, mostly male, and this gender correlates to most other dimensions. Curvy and colorful drones were most likely to seen as feminine, which reminds us of the female body shape and makes us wonder about the potential correlation between drones and human-likeness. We were surprised to find a moderate correlation between feminine and animal-like drones. We found that drones could be precisely located on a fine-grained spectrum from machine-like to animal-like. Prior work with ground robots [27, 48] suggest that high anthropomorphization - human-likeness in their studies - correlates with higher rankings in sociability and intelligence. In our work, we find equivalent findings for sociability where high ratings in animal-likeness correlate with friendliness, interaction, and likeability. However, we did not find a correlation between animal-likeness and intelligence. These findings suggest that the differences between ground and flying robots need to be further investigated.

6.4 Implications for Ubiquitous Computing

Ubiquitous computing started with shared displays and continued with the rise of personal computing from laptops to mobile and wearable devices. As robots and drones become increasingly present in our environments, they become part of it, and by definition ubiquitous. Whether a person is using a personal drone for taking photos when traveling, or using a drone as a delivery service, many will be confronted to these technologies. Some of these interactions will be desired, while some may not. It is therefore critical that we better understand how these new technologies fit in our every day lives and how people think about them and understand their actions and behaviors. Ubiquitous Computing research should increase its focus on intelligent agents to better understand metrics such as trust in future devices design. This work is a first step towards understanding how people perceive these new flying technologies.

7 LIMITATIONS

We built a dataset of commercial drone pictures using all the quadcopters we could find online a month prior to our study in July 2018. As drones continue to expand their reach, more drones will populate the dataset. As they increase their capabilities, more features might need to be coded in. At the time of the study, only a limited number of drones were designed with animal-like features, which created an unbalanced dataset. Additionally, we did not study the influence of the size of the drone since many of the drones found did not include any information as to their real size. In this work, the evaluation of the drones design is based on still images of the drones as in [27, 38]. There are however additional factors that will come into play when a person is collocated with a drone and which may affect how it is perceived, including: the drone size [8]; number of propellers [3]; movement and flight path [7, 24, 66]; noise [3, 8]; and distance to a person [66, 70]. Specifically, depending on the distance and position of a flying drone, a person might not be able to see all of their features. While our work is limited to studying still images, it represents a first step in better understanding how these devices are perceived.

8 FUTURE WORK

Much prior work in robotics cited, discussed, or investigated the Uncanny Valley theory. Yet, it has only been tested empirically by a small number of studies, often leading to contradictory results. Inspired by Mathur and Reichling's work [38], we used an objective selection process to obtain a large number (63) of real-world drones. Empirically, we estimated the perceived animal-likeness of each drone image, and were able to precisely locate them on a fine-grained spectrum from machine-like to animal-like. Using the median scores attributed by participants, we find that the third-degree polynomial regression representing the relationship between animal-likeness and interaction shows the two inflection points defining the Uncanny Valley theory [37] with $R^2_{Adj} = 0.12$, p<0.05 (Figure 3). We also see the two inflection points when comparing the relationship between animal-likeness and friendliness $R^2_{Adj} = 0.42$, p<0.001. Using AIC estimate we find that in both cases the third-degree polynomial fits better than the other models with higher (up to forth) or lower polynomial degrees – AIC scores were, from the linear fit to the forth-degree polynomial: 394.4, 393.9, 389.0, 390.1.

Both interaction and friendliness increase up to a certain point and then decrease (drones #5 and #6). When the drones start to look like an animal, the values increase again positively (drones #1 to #4). Figure 3 shows the fitted curve for interaction from machine-likeness to animal-likeness. These results suggest the presence of an

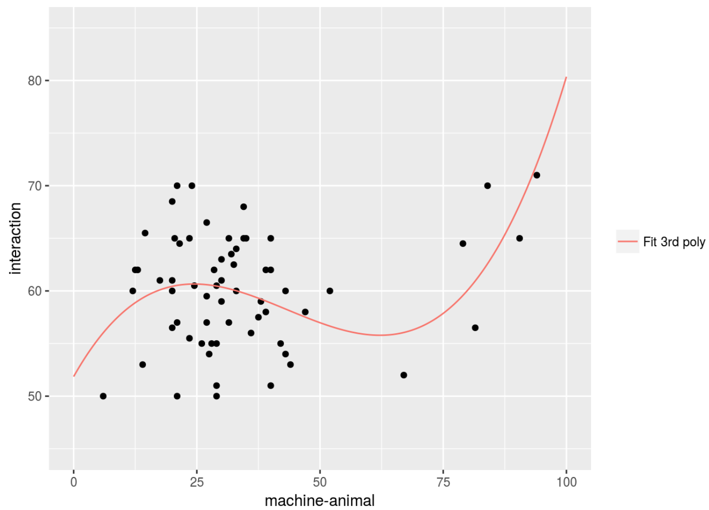

Fig. 3. Is there an Uncanny Valley phenomena in drones? The graph shows how much people want to interact with a drone from machine-like to animal-like. The red curve represents the polynomial regression 3rd order.

Uncanny Valley in drones that are animal-like. This is in line with a recent study [53] which indicates that the uncanny valley phenomena may also exist for animal-like virtual characters.

This results are surprising given that most drones are not currently designed for social interactions and are mostly non-anthropomorphic in design. While our regression shows statistical significance in interaction and friendliness, these results are still preliminary on a small sample which is not well balanced. We hope that future researchers will continue our efforts in this direction. Additional future work should investigate whether experience with drones and/or robots, skills, personality types, and cultures, may lead to people perceiving the drones differently. As an increasing amount of drones are being sold worldwide, new models will be added to our dataset, so that new features can also be studied. In the future, we will further investigate how other properties of the drones affect people's perceptions and willingness to interact, including movements, speed, noise, and size.

9 CONCLUSION

This work aimed to further our understanding of how drones are being perceived based on their design. This paper addressed the results of an Amazon Mechanical Turk user study (N=307) demonstrating how people perceive drones across eight dimensions: Animal likeness, Friendliness, Intelligence, Trustworthiness, Age, Gender, Interaction, and Likeability. We described empirical findings on how people perceive drones depending on their position on the machine-likeness to animal-likeness spectrum, as well as how individual design characteristics impact perception. Our findings highlight that current security measures are counteractive with regards to trust perception. This research contributes a dataset of 63 drone images coded along 10 features. We also contribute a regression model that can be used to infer which drone physical features elicit particular responses. This work opens up the space of drone perception and how to design them in the future. Our dataset is available online at http://drone-design.net/ including summaries, statistics, and the ability to add new drones to the dataset.

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