Technology in Society 77 (2024) 102533

Contents lists available at ScienceDirect

Technology in Society

journal homepage: www.elsevier.com/locate/techsoc

# Trust in artificial intelligence, trust in engineers, and news media: Factors shaping public perceptions of autonomous drones through UTAUT2

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ARTICLE INFO

*Keywords:*
Trust in AI
Trust in AI engineers
News media attention
Attitude
Public perceptions
UTAUT2

ABSTRACT

Traditional trust in artificial intelligence (AI) scholarship has assumed trust as an attitude placed exclusively in the AI system. We offer a more articulated view of trust in AI, extending the extended Unified Theory of Acceptance and Use of Technology (UTAUT2) model by integrating news media attention, trust in AI system, trust in AI engineers, and attitude to examine factors predicting public's intention to use autonomous passenger drones. Based on an online survey of adult Singaporeans ($N = 1002$), results from hierarchical OLS regression analyses demonstrated the direct effects of news media attention, trust in AI system, and attitude, alongside several UTAUT2 constructs, on use intention. Results of subsequent mediation analyses using structural equation modelling between trust in AI system, trust in AI engineers and use intention through attitude were consistent with a partial and full mediation effect, respectively. Notably, both trust constructs were influenced by news media attention in comparable magnitudes. In this sense, trust placed in AI system can be seen separately from that placed in engineers responsible for AI development. Furthermore, we found support for including attitude in the UTAUT2 main model for emerging technologies in which information and practice remain largely inaccessible to the public. Theoretical and practical implications are discussed.

Engineers continue to develop artificial intelligence (AI) into more advanced forms, moving away from symbolic (i.e., rule-based) AI and closer to a robust AI with a "hybrid" approach. AI systems for autonomous driving are on path to becoming capable of making decisions based not only on laws of physics, trained in a confined location, but also real-time physical data gathered unconstrained by geography through various sensors on agents such as autonomous vehicles and drones [1]. These breakthroughs made approaching AI from the perspective of the conventional communication viewpoint problematic, because AI has transformed itself to not be a communicative tool between humans but rather a decision maker itself, functioning as a "quasi-human partner" ([2], *p.* 116).

Indeed, as AI systems have the potential to effectively serve as drivers and pilots, public perceptions become imperative. However, the AI perception literature is challenged in several aspects. First, scholars have traditionally assumed trust as an attitude placed only in the AI system and failed to recognize its complexities (e.g., Ref. [3–5]). For the most part, many of the instruments ignored that trust is an intrinsically complex construct in which multiple dimensions are involved. As AI systems become more versatile, they require different value judgements, knowledge levels, and expectations to form trust. These instruments were also designed to evaluate trust levels after participants had some experience interacting with the AI systems. This is undesirable for perception studies because these are emerging technologies, thus are largely out of reach to the public. Indeed, most studies examined trust in terms of trust in the system per se. As the advancement of deep learning has made it possible for the system to make decisions on and by itself, the "black box" challenge is present not only to end users but also to its developers [6]. We therefore propose to conceptually distinguish between trust placed in the AI systems and that in the AI engineers. Second, previous perception studies have not examined the mechanisms to which cognitive and affective factors have on public perceptions of AI systems in autonomous driving (e.g., Ref. [7,8]). Even when these mechanisms were explored, media effects were not examined (e.g., Ref. [9,10]). Indeed, the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003) and its extended version, the extended Unified Theory of Acceptance and Use of Technology (UTAUT2) [11] appropriated by several AI perception studies (e.g., Ref. [3,12]) excludes several important constructs that pertain to AI applications, such as news media attention. As AI is evolving by the day

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https://doi.org/10.1016/j.techsoc.2024.102533
Received 29 September 2023; Received in revised form 15 February 2024; Accepted 23 March 2024
Available online 29 March 2024

and that news media, including social media news, may be the main source of information for the public, news media attention to AI-related news may play an important role in shaping various cognitive and affective states associated with users' behavior. Finally, the exclusion of attitude from the main model of UTAUT [13] in traditional UTAUT2 scholarship may not be justified with emerging technologies that are inaccessible to the public. As the public may not have enough experience and thereby information at hand to form perceptions along the lines of UTAUT2 constructs, the inclusion of attitude in the main model may be necessary to capture factors that influence use intention that are not articulated in UTAUT2.

Against this backdrop, this study builds on UTAUT2 [11] to examine the predictive values of news media attention, trust in AI system, trust in AI engineers, and attitude. Subsequent mediation analyses were conducted to examine the relationships between these extended constructs. The mediation model examined how news media attention affected trust constructs, and thereby use intention through attitude. We found direct effects of news media attention, trust in AI system, and attitude on public perceptions using the UTAUT2 framework. Subsequently, we found support for trust in AI to be seen separately in terms of trust placed on the AI system, and that placed on the AI engineers. More concretely, news media effects influenced both types of trusts which would be instrumental in predicting public perceptions of emerging AI technologies such as autonomous passenger drones. The results for the mediation effect between trust in AI system, trust in AI engineers and use intention through attitude were consistent with a partial and full mediation effect, respectively.

## 1. Literature review

### 1.1. Autonomous passenger drones

As an emerging technology, autonomous passenger drones have yet to pick up research momentum in the social sciences realm and is thereby not well defined in the field. This technology may be termed as "drone taxis" (e.g., Ref. [14]), "flying taxis" [15,16], passenger drones (e.g., Ref. [17]), or "drones for passenger transportation" (e.g., Ref. [18]), none of which explicitly states the AI-driven or autonomous feature. In the absence of a proper and unified definition, the present study defines autonomous passenger drones as *vehicles in the air which can operate fully autonomously with artificial intelligence (AI) technology and without human intervention in executing the flight mission for the purpose of human transportation from location to location*. This definition was developed with reference from legal definitions by the European Union [Article 2(17); 3(30)] [19,20], which had been reviewed and refined by engineering scientists researching and developing AI systems in drone applications.

### 1.2. The Singapore case

In Singapore, passenger drones are expected to be launched as soon as 2024. In preparation for the introduction of passenger drones, the Singaporean government has been actively developing legal and regulation guidelines and personnel training [16]. Although the drones are equipped with autonomous flying systems, they are expected to be piloted by a human, mainly because of societal concerns [16,21]. The drones will be used for touristic purposes at the beginning, with plans to expand to other applications such as cross-city commute. Nevertheless, the technology is being researched and developed in various countries and is expected to be the future of urban air mobility [22]. For this reason, the present study sets out to investigate the current state of public perceptions toward autonomous passenger drones prior to its introduction, in which the findings may be informative to other countries with similar plans if corroborated with the public's actual use behavior and support following the actual introduction.

It is noteworthy that civilian drone use is largely regulated in Singapore. Drones can be legally purchased and operated with permits in compliance with safety measures. People who use drones without proper permits will be penalized. For example, a person operating a photography drone without permits could be fined an amount of SGD 5000 (approx. USD 3720) [23]. Nevertheless, Singapore remains a highly advanced society that harnesses new technologies. Apart from passenger drones, the country has been actively laying the groundwork for various AI-powered technologies, such as autonomous vehicles [24] and automation systems [25]. The Singaporean government has plans in place to develop the country into a leader in AI technologies by 2030 [26].

### 1.3. Theoretical background

UTAUT2 is a theoretical model that examines factors associated with technology adoption and has been used in studies of 5G technology [27], augmented reality [28], and AI application [12]. It measures seven basic constructs and their influence on technology adoption, which accounted for 56 to 74 percent of the variance [29]. The UTAUT2 is an extension of the original UTAUT model, where eight technology acceptance models had been reviewed and integrated. These models included, "Theory of Reasoned Action, the Technology Acceptance Model, the Motivational Model, the Theory of Planned Behavior, a model combining the Technology Acceptance Model and the Theory of Planned Behavior, the Model of PC Utilization, the Innovation Diffusion Theory, and the Social Cognitive Theory" ([13], p. 425). In UTAUT2, an additional three constructs were integrated, and the moderator of voluntariness of use was dropped, which resulted in a total of seven basic constructs and three moderators. This extension was conducted primarily so that the model could be adopted in the context of consumer use rather than organizational use of technology [11].

The seven basic constructs are: 1. *performance expectancy*, "the degree to which using a technology will provide benefits to consumers in performing certain activities"; 2. *effort expectancy*, "the degree of ease/effort associated with consumers' use of the technology; 3. *social influence*, the degree to which "the consumers perceive that important others (e.g., family and friends) believe that they should use a particular technology"; 4. *facilitating conditions*, "the customers' perceptions of the resources and support available to perform a behavior"; 5. *hedonic motivation*, "the fun or pleasure derived from using a technology"; 6. *price value*, the "customers' cognitive tradeoff between the perceived benefits of the applications and the monetary cost for using them; and 7. *habit*, the "extent to which people tend to perform behaviors automatically because of learning" ([11], p. 159, p. 161).

The UTAUT2 offers a robust and appropriate framework to examine public perceptions of autonomous passenger drones. Primarily, the UTAUT2 is a comprehensive framework with a wider range of constructs. This offers an advantage to our research as our study context – autonomous passenger drones – is an emerging technology that is yet to be introduced to the public. Hence, we are able to investigate which constructs can exert influences on use intention at the current stage. For this reason, it is common for scholars to remove constructs and/or test extended constructs to adapt to the study context, despite the framework's robustness (e.g., Ref. [12,28,30,31]). We expect that the predictive values of each basic construct may vary and fail to predict use intention in some respects but not in others, especially as this study intends to extend the model with trust constructs in which predictive value may be strong enough to dominate the main effects. The nature of this examination therefore remains exploratory. The following research question is put forth for examination:

**Research Question**: What are the predictive values of the UTAUT2 constructs on intention to use autonomous passenger drones?

### 1.4. Trust in AI system

The trust in AI scholarship largely agrees with Lee and See [32]'s definition where trust is defined as "the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability," ([32]. p. 51) which highlights the situation where the AI technology inevitably brings, that is, uncertainty and vulnerability. A similar definition with these elements was offered where trust was defined as "a mental state that A [the trustor] holds toward B [the trustee] with respect to the performance of [a behavior]" ([33], p. 1441). This definition is more appropriate in the language sense because it describes trust as a mental state, rather than an attitude. A mental state may denote momentary changes, whereas an attitude may not necessarily change in short instances. Indeed, trust appears to be a mental state that can change anytime not only as users experience the technology but prior to and following the use experience. In this light, the present article defines trust with Chen [33]'s definition integrating uncertainty and vulnerability. That is, trust is referred to as *a mental state that the trustor holds toward the trustee with respect to the performance of a behavior in uncertainty and vulnerability*.

The trust construct has been important in predicting use of new technologies where knowledge levels remain low. This is particularly important in automation, a technology that minimizes human input in performing tasks that are traditionally carried out by human [32]. Trust has been examined in perceptions of AI technologies because of the uncertainty involved in the decision-making process. For example, there have been empirical studies on AI technologies incorporating trust in the Technology Acceptance Model (TAM) [34–36]. When stakes are higher, trust becomes more relevant. Trust was reported to be the most robust factor determining the adoption of autonomous vehicles in a number of studies (e.g., Ref. [37]; [38]). This pattern was also observed in a meta-analysis examining factors predicting autonomous vehicles adoption [39].

Similarly, trust is an important factor for a passenger to use the drone. If complete automation by the AI system is achieved, passengers in drones always bear more risks than passengers in autonomous vehicles because when accidents take place in the sky, they are more likely to be fatal, even for an experienced user [40]. If autonomous passenger drones carry only passengers, trust is a necessary predisposition because, unlike autonomous vehicles, the passengers are not able to intervene in emergencies. Furthermore, AI is often referred to as a "black box" [41], because the decision-making process is not made known to the end users. Trust is then an important consideration for passengers as they are put in a vulnerable position where risks are involved.

However, the trust in AI scholarship has faced problematic trust operationalization. First, perhaps trust is a concept intuitive enough, many studies included self-developed 1-item or 2-item Likert-type instruments on the question "how much do you trust (the system)" (e.g., Ref. [42–48]). Second, these instruments have a tendency to focus on the ability aspect of the AI systems (e.g., Ref. [3–5]) and ignore other factors. For example, as safety issues have been a top concern in the adoption of autonomous vehicles [49], it seems important for the user to trust the AI system to execute its mission in a safe manner. At first glance, this overlaps with trust in the ability because when one asks whether the AI system can carry out its mission *successfully*, it implies that it is to be carried out *safely*. However, it does not always follow that a mission carried out successfully must be a mission carried out safely to the users. In fact, the algorithms associated with the AI may decide to carry out the mission *successfully* at the expense of *safety*, which is where the values of the AI system come into play. Third, a number of studies deployed instruments of trust designed for people with experience with the system, that is, the measuring of *learned trust* (e.g., Ref. [46–48]). This is undesirable for public perception studies because a new technology such as autonomous passenger drones have not been widely introduced and many in the public have not been exposed to this technology.

From a conceptual standpoint, trust in AI system can be seen in terms of the *trustworthiness* of the agent. While trust is the mental state that the trustor holds toward the trustee with respect to the performance of a behavior in uncertainty and vulnerability, *trustworthiness* is defined as "the quality in [the trustee] that satisfies this mental state" ([33], p. 1441). In other words, it is the trustworthiness in the AI system that satisfies trust by the user. Trustworthiness is widely conceptualized with the factors of *ability*, *benevolence*, and *integrity* in the organizational trust model [50]. These factors were later adapted in automation with performance, purpose, and process corresponding to ability, benevolence, and integrity respectively [32]. *Performance* is "the current and historical operation of the automation … [and] describes what the automation does" (p. 59). The performance factor includes not only the ability of the automation, but also reliability or predictability, because automation can be inconsistent. We include therefore the trustworthiness factor of reliability, that is, "the extent to which [the trustee] responds similarly when it encounters similar circumstances at different points in time" ([51]. p. 439). *Purpose* is "the degree to which the automation is being used within the realm of the designer's intent" ([32], p. 59). This definition does not differentiate between trust placed in the system and its developers (as we make the case in the following section), therefore we define purpose as the degree to which the AI system is operating in good faith and intent. *Process* is "the degree to which the automation's algorithms are appropriate for the situation and able to achieve the operator's goals … [and] describes how the automation operates" (p. 59). We therefore conceptualize trust in AI system as its trustworthiness factors including performance, process, and purpose. Taking these into account, we hypothesize:

**Hypothesis 1**. Trust in AI system is positively associated with intention to use autonomous passenger drones.

## 2. Trust in AI engineers

As we stated, scholars have embraced the idea that trust in AI is trust placed only in the AI system. We now attempt to make the case of why this is problematic for perception studies. First, the AI as "black box" metaphor applies not only to end users but in many instances the engineers. With the advancement of deep learning technologies [52], AI systems may make decisions on their own that even the engineers who developed the systems are unaware of [6]. For example, engineers working in major technological companies have indicated that they do not fully understand how the AI-driven conversational generative chatbot they developed works [53]. In other words, deep learning has made it possible for the AI system to learn by itself and may produce output on its own, unintelligible to engineers. With the use of deep learning becoming more prevalent in AI applications, it is therefore imperative to differentiate conceptually between trust placed in the AI system and in the engineers who developed the AI systems.

Moreover, trust in engineers can form public perceptions in AI due to the algorithmic unfairness problem [54]. For example, algorithms designed for facial recognition may have difficulty identifying non-Caucasian faces, as well as identifying black people as gorillas [55, 56]. This presents a major challenge to users' trust because AI systems in autonomous driving and flying depend on the accuracy of object detection to make decisions. Indeed, algorithms are not intrinsically sexist, racist, or ageist, and the biases may be traced back to the coding and programming processes. Human bias can be present in the selection of engineers (i.e., whether the engineers are demographically diverse enough to consider data biases affecting minorities), the training of the data (i.e., whether the selected data to be trained avoids stereotyping in the AI application behaviours), and the defining of the desired output (i.e., whether the values of the persons and objects are defined in a fair and unbiased manner) [57].

Scholars have proposed that trustworthiness factors are not relevant only to the technological tool itself, but also among stakeholders such as key individuals, groups, and institutions [58]. Indeed, when a new technology is introduced, people may reject it if the developers behind it are untrustworthy to the public [59]. Similarly, as a general trait, deference to scientific authority also predicted public adoption of emerging science and technologies [60,61]. Some studies have begun to look into credibility of the technology itself as well as the firm or developers [62]. In a recent study, trust in the autonomous vehicle itself has direct effects on use intention, whereas trust in the manufacturers had an indirect effect through privacy risks [63]. It appears therefore that trust in engineers may carry some predictive values in the intention to adopt AI applications. Engineers are here defined as experts who engage in programming and coding of the algorithms from its associated artificial intelligence system. It is noticeably distinct from developers and manufacturers representing the firm, which can include non-engineering personnel such as the board, management employees, and salespersons. With these, we hypothesize:

**Hypothesis 2**. Trust in AI engineers is positively associated with intention to use autonomous passenger drones.

### 2.1. News media attention

As experience and knowledge of new technology remains low, news media reporting often plays an important role in facilitating or impeding adoption. For this reason, media effects were examined in the adoption of new technologies, especially controversial ones such as biotechnology [64], embryonic stem cell technology [65], and nanotechnology [66]. In terms of AI applications, Ho et al. [60] found that news media attention directly predicted willingness to use autonomous vehicles, but it did not explore how this effect took place. Another study on autonomous vehicles reported that attention to mass and social media predicted perceived usefulness and perceived risks, and thereby intention to use [67]. Similarly, mass media and social media were also reported to influence trust, both directly and indirectly, through self-efficacy in autonomous vehicles [38,68]. It seems therefore that news media attention may have resulted in enhanced knowledge of the technology and thereby influencing intention to use. This enhanced knowledge on the subject matter may yield various cognitive and affective mechanisms through which use intention is affected. It is reasonable to expect that trust, as the most robust predictor in predicting autonomous vehicle use, should carry similar weights as other cognitive perceptions.

Furthermore, the media landscape in Singapore generally offers neutral and factual reporting as it is highly regulated by the authorities [69]. A content analysis of news articles of autonomous vehicles in Singapore demonstrated that the reporting is predominantly positive and neutral [60]. In the present study, we similarly conducted a content analysis of news articles on passenger drones and found that the reporting tone for all news articles was positive/neutral.[1] As such, we hypothesize:

**Hypothesis 3**. News media attention is positively associated with intention to use autonomous passenger drones.

**Hypothesis 4a**. The relationship between news media attention and intention to use autonomous passenger drones is mediated by trust in system.

**Hypothesis 4b**. The relationship between news media attention and intention to use autonomous passenger drones is mediated by trust in engineers.

### 2.2. Attitude

Even though attitude was present in several theoretical models that UTAUT2 consolidated, it was removed from the main model because it was argued to be a result of various constructs as its effect had been explained away in the presence of UTAUT constructs [13]. Nevertheless, attitude has been widely recognized as a robust direct predictor on intention to use in various theoretical models such as the Technology Acceptance Model, the Theory of Reasoned Action, and the Theory of Planned Behavior [70,71]. As autonomous passenger drones remain an emerging technology out of public reach, a few critical information associated with UTAUT2 constructs are unknown to the public. For example, price value, facilitating conditions, and effort expectancy require concrete knowledge of the technology that may only be accessible after its deployment. Many autonomous vehicle perception studies have addressed this issue by modifying and excluding certain constructs (e.g., Ref. [7,72]). Indeed, this practice is so common in UTAUT2 studies that scholars have questioned the necessity of some constructs (e.g, Ref. [73,74]). It may be challenging to gauge public perceptions in terms of the UTAUT2 constructs alone as the public may have formed perceptions of the technology with factors outside the framework. In this sense, including attitude as a direct predictor in UTAUT2 may be necessary at least for emerging technologies such as autonomous passenger drones. Furthermore, as critical precursors to use AI applications, the cognitive and affective states of trust in system and engineers should be appropriate constructs to influence attitude toward autonomous passenger drones. Indeed, the TAM perspective suggests that attitude remains a mediator between perceptions and use intention. The role of attitude outside UTAUT2 and its relationship with other constructs deserves attention. As such, we hypothesize:

**Hypothesis 5**. Attitude is positively associated with intention to use autonomous passenger drones.

**Hypothesis 6a**. The relationship between trust in system and intention to use autonomous passenger drones is mediated by attitude.

**Hypothesis 6b**. The relationship between trust in engineers and intention to use autonomous passenger drones is mediated by attitude.

Hypotheses 3, 4a, 4b, 5, 6a, and 6b form a mediation theoretical model and is presented in Fig. 1.

### 2.3. Research methodology

#### 2.3.1. Data collection

We engaged Rakuten Insight, a research firm, to conduct an online survey with the general public between April 28, 2023, and May 17, 2023, in Singapore. Inclusion criteria included: 1. Singaporean or permanent resident in Singapore, and 2. aged 21 or above. Distribution of samples were set according to the population distribution in Singapore in terms of age, gender, and ethnicity. Stratified sampling was used because Singapore is a multi-racial country to ensure representativeness. Respondents who completed the survey received a compensation according to the terms of Rakuten Insight. All items in the survey questionnaire were rated on a 5-point Likert, Likert-type, or semantic differential scale. Prior to responding to questions related to autonomous passenger drones, respondents were shown the conceptual definition where autonomous passenger drones were defined as "vehicles in the air which can operate fully autonomously with artificial intelligence (AI) technology and without human intervention in executing the flight mission for the purpose of human transportation from location to location," in conjunction with a brief description of AI and its associated algorithms. A timer was placed on the definition page and required respondents to stay on for at least 30 seconds before they could proceed to the main questionnaire.

[1] A content analysis on news articles was conducted for this study. First, we extracted all the news articles on passenger drones reported by *The Straits Times*, *Business Times Singapore*, and *TODAY* from Factiva. The search terms included passenger drone OR flying taxi OR drone taxi OR taxi drone AND Singapore. This resulted in 17 unique news articles. Two independent coders analyzed the tone of the articles (intercoder reliability: $r = 1.00$).

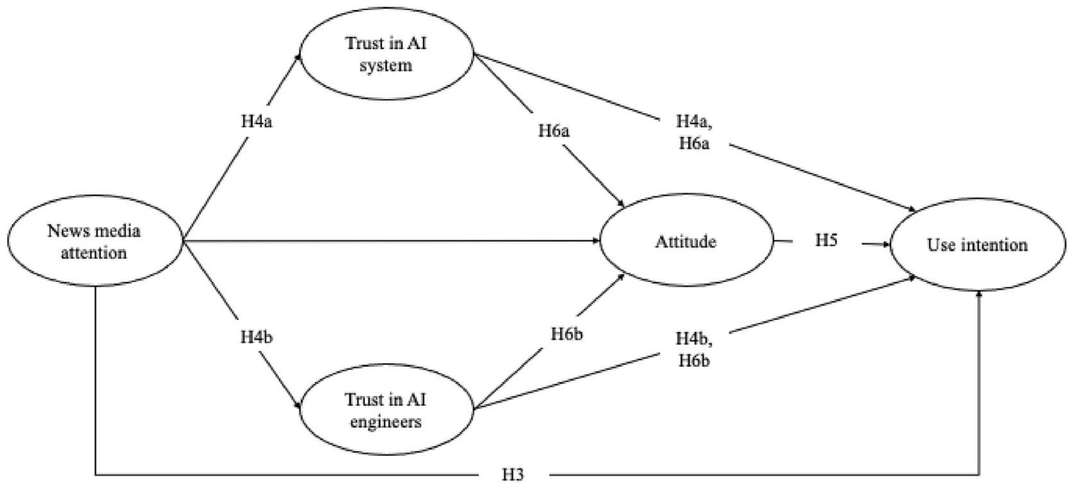


**Fig. 1.** Hypothesized mediation model.

#### 2.3.2. Participants

A total of 1002 participants were recruited in Singapore. There were 910 Singaporeans (90.8%) and 92 permanent residents (9.2%) in the sample. We collected stratified samples so that gender, age, and ethnicity were distributed according to the latest population distribution in Singapore. Specifically, there were 493 men (49.2%) and 509 women (50.8%). The samples were predominantly Chinese ($n$ = 746; 74.4%), followed by Malay ($n$ = 140; 14.0%), Indian ($n$ = 85; 8.5%), and others ($n$ = 31; 3.1%). There were 159 participants aged between 21 and 29 (15.9%), 176 participants aged between 30 and 39 (17.6%), 184 participants aged between 40 and 49 (18.4%), 195 participants aged between 50 and 59 (19.5%), 89 participants aged between 60 and 64 (8.9%) and 199 participants aged 65 or above (19.9%). In terms of education levels, 7 participants did not receive formal education (0.7%), 7 participants completed primary education (0.7%), 44 participants completed secondary education (4.4%), 47 participants completed N-level (4.7%), 88 participants completed O-level (8.8%), 41 participants completed A-level (4.1%), 228 participants obtained diploma and professional qualifications (22.8%), 423 participants obtained bachelor's degree (42.3%), 102 participants obtained master's degree (10.2%), and 15 of them obtained doctoral degree (1.5%). In terms of household income, 282 of the samples (32.0%) had a monthly household income below $5000 (~ USD 3716), 339 of them (33.9%) between $5000 and $10,000 (~ USD 3716–7433), 174 of them (17.3%) between $ 10,000 and $ 15,000 (~ USD 7433–11,149), 118 (11.8%) of them between $15,000 and $20,000 (~ USD 11,149–14,866), and 50 (5.0%) of them above $20,000 (~ USD 14,866).

#### 2.3.3. Instruments

*UTAUT2 constructs.* UTAUT2 constructs were measured using various scales adapted for measuring adoption of AI technologies [12]. Performance expectancy was measured by 3 items ($M$ = 3.64; $SD$ = 0.71; Cronbach's α = 0.88). Effort expectancy was measured by 4 items ($M$ = 3.40; $SD$ = 0.72; Cronbach's α = 0.89). Social influence was measured by 3 items ($M$ = 3.19; $SD$ = 0.84; Cronbach's α = 0.91). Price value was measured by 3 items ($M$ = 3.25; $SD$ = 0.82; Cronbach's α = 0.88). Hedonic motivation was measured by 4 items ($M$ = 3.49; $SD$ = 0.80; Cronbach's α = 0.92). Facilitating conditions was measured by 3 items ($M$ = 3.34; $SD$ = 0.77; Cronbach's α = 0.87). Habit was measured by 3 items ($M$ = 3.26; $SD$ = 0.82; Cronbach's α = 0.88).

*Trust in AI system.* Trust in AI system ($M$ = 3.38; $SD$ = 0.61) was measured by Likert scales for adapted drones [75] which included the performance (ability; 4 items), process (4 items), and purpose (4 items) dimensions. The performance dimension also included the reliability sub-dimension which was measured by two adapted items [37] and two self-developed items of the same scoring structure that captured the consistency of behaviors in the AI systems (4 items). Internal reliability was satisfactory (Cronbach's α = 0.95).

*Trust in AI engineers.* Trust in AI engineers ($M$ = 3.50; $SD$ = 0.61) was measured by adapted Likert scales [76] which included the ability (4 items), benevolence (4 items), and integrity (4 items) dimensions. A definition of engineers was provided at the beginning of the scale, showing that "engineers are experts who engage in programming and coding of the algorithms from its associated artificial intelligence (AI) system." Internal reliability was satisfactory (Cronbach's α = 0.93).

*News media attention.* News media attention ($M$ = 2.91; $SD$ = 1.01) was measured using a Likert-type scale in which respondents rated their attention to autonomous passenger drones across TV news, printed news, online news, and social media. We have chosen to measure news media attention with these items as they were consistent with prior studies (e.g., Ref. [61,65]). Internal reliability was satisfactory (Cronbach's α = 0.89).

*Attitude.* Attitude ($M$ = 3.53; $SD$ = 0.71) was measured using the Emerging Technologies Semantic Differential Scale (ETSDS; 9 items) [77]. The scale consisted of the question "when you think about AI drones, please indicate the position on the scale that best represents the direction and intensity of your judgement," to which sample items included "safe/unsafe", "good/bad", and "reliable/unreliable." We removed 2 items with low factor loadings of 0.50 from all analyses. Internal reliability was satisfactory with the remaining items (Cronbach's α = 0.84).

*Intention to use.* Use intention ($M$ = 3.27; $SD$ = 0.85) was measured by a 3-item scale adapted for measuring adoption of AI technologies [12]. Internal reliability was good (Cronbach's α = 0.91).

*Demographics.* Age, gender, ethnicity, previous use of civilian drones, education level, marital status, and household income were measured.

Exact item wording, factor loadings, and descriptive statistics are presented in Table 1.

## 3. Results

### 3.1. Correlation analyses

A Pearson's correlation analysis was conducted on SPSS 26.0. All variables presented positive and significant correlations, providing preliminary evidence for the hypotheses. The zero-correlation matrix is presented in Table 2.

**Table 1**
Exact item wording, factor loadings, and descriptive statistics.

| Instrument items | *Factors* | *CR* | *AVE* | *α* | *M* | *SD* |
|---|---|---|---|---|---|---|
| **News media attention** | | 0.90 | 0.69 | 0.89 | | |
| On a scale of 1–5 (1 = No attention at all, 5 = A lot of attention), how much attention do you generally pay to (the following sources) about autonomous passenger drones? | | | | | | |
| TV news | 0.90 | | | | 2.95 | 1.12 |
| print newspapers | 0.86 | | | | 2.80 | 1.20 |
| online news | 0.89 | | | | 3.02 | 1.13 |
| social media | 0.67 | | | | 2.87 | 1.19 |
| **Trust in AI system** | | 0.96 | 0.57 | 0.95 | | |
| On a scale of 1–5 (1 = Strongly disagree, 5 = Strongly agree), to what extent do you agree or disagree with the following statements about an autonomous passenger drone that is enabled by the artificial intelligence (AI) system? | | | | | | |
| *Performance* | | | | 0.90 | | |
| The AI system in autonomous passenger drones will be competent and effective at assisting in transporting people. | 0.72 | | | | 3.51 | 0.73 |
| The AI system in autonomous passenger drones will perform its role of transporting people very well. | 0.70 | | | | 3.42 | 0.74 |
| Overall, the AI system in autonomous passenger drones will be a capable and proficient means for transporting people. | 0.70 | | | | 3.45 | 0.77 |
| In general, the AI system in autonomous passenger drones will be very knowledgeable about transporting people. | 0.76 | | | | 3.43 | 0.78 |
| *Reliability* | | | | | | |
| I believe that I can form a mental model and predict future behavior of the AI system in autonomous passenger drones. | 0.68 | | | | 3.25 | 0.88 |
| I believe that I can predict how the AI system in autonomous passenger drones will act in a particular way. | 0.68 | | | | 3.21 | 0.89 |
| I believe that the AI system in autonomous passenger drones will carry out its mission successfully in a consistent way. | 0.75 | | | | 3.44 | 0.80 |
| I believe that the AI system in autonomous passenger drones will be consistent in terms of its ability. | 0.76 | | | | 3.49 | 0.78 |
| *Purpose* | | | | 0.86 | | |
| I believe that the AI system in autonomous passenger drones will operate in my best interest. | 0.80 | | | | 3.42 | 0.82 |
| If I require help, the AI system in autonomous passenger drones will do its best to help me. | 0.79 | | | | 3.40 | 0.81 |
| The AI system in autonomous passenger drones will be concerned about my well-being, not just its own. | 0.74 | | | | 3.29 | 0.87 |
| The AI system in autonomous passenger drones will be concerned about the well-being of the pedestrians on the ground. | 0.75 | | | | 3.37 | 0.82 |
| *Process* | | | | 0.88 | | |
| The AI system in autonomous passenger drones will be consistently truthful in its communication with me. | 0.82 | | | | 3.41 | 0.81 |
| I will characterize the AI system in autonomous passenger drones as honest. | 0.85 | | | | 3.39 | 0.81 |
| The AI system in autonomous passenger drones will be consistently sincere and genuine. | 0.83 | | | | 3.36 | 0.81 |
| I believe the AI system in autonomous passenger drones will always be concerned of my well-being. | 0.79 | | | | 3.28 | 0.83 |
| **Trust in AI engineers**[a] | | 0.95 | 0.60 | 0.93 | | |
| On a scale of 1–5 (1 = Strongly disagree, 5 = Strongly agree), to what extent do you agree or disagree with the following statements? | | | | | | |
| *Ability* | | | | 0.88 | | |
| Engineers are very capable of developing autonomous passenger drones. | 0.73 | | | | 3.65 | 0.75 |
| Engineers are known to be successful at developing autonomous passenger drones. | 0.78 | | | | 3.55 | 0.80 |
| I feel very confident about engineers' skills in developing autonomous passenger drones. | 0.85 | | | | 3.48 | 0.83 |
| Engineers are well qualified to develop autonomous passenger drones. | 0.82 | | | | 3.57 | 0.79 |
| *Benevolence* | | | | 0.86 | | |
| Engineers are very concerned about my welfare when they are developing autonomous passenger drones. | 0.81 | | | | 3.43 | 0.83 |
| My safety and privacy are very important to engineers developing autonomous passenger drones. | 0.73 | | | | 3.60 | 0.84 |
| Engineers of autonomous passenger drones will not knowingly do anything to harm me. | 0.72 | | | | 3.56 | 0.78 |
| Engineers really look out for what is important to me when developing autonomous passenger drones. | 0.79 | | | | 3.50 | 0.81 |
| *Integrity* | | | | 0.85 | | |
| Engineers have a strong sense of ethics as they develop autonomous passenger drones. | 0.77 | | | | 3.42 | 0.78 |
| I never have to wonder whether engineers will be ethical as they develop autonomous passenger drones. | 0.67 | | | | 3.30 | 0.86 |
| I like the engineers' values in developing autonomous passenger drones. | 0.77 | | | | 3.43 | 0.77 |
| Sound principles seem to guide engineers' behavior in | 0.81 | | | | 3.49 | 0.78 |

(*continued on next page*)

**Table 1** (*continued*)

| Instrument items | *Factors* | *CR* | *AVE* | *α* | *M* | *SD* |
|---|---|---|---|---|---|---|
| developing autonomous passenger drones. | | | | | | |
| **Attitude** | | 0.84 | 0.44 | 0.85 | | |
| Below is a list of 9 polar opposite adjectival pairs on a 5-point scale. When you think about autonomous passenger drones, please indicate the position on the scale that best represents your judgment. | | | | | | |
| Safe – Unsafe | 0.55 | | | | 3.23 | 1.07 |
| Meaningless – Meaningful | 0.68 | | | | 3.50 | 1.00 |
| Inspiring – Uninspiring | 0.51 | | | | 3.53 | 1.04 |
| Tedious – Interesting | 0.63 | | | | 3.53 | 1.02 |
| Innovative – Outdated (Removed) | – | | | | 3.78 | 1.06 |
| Bad – Good | 0.80 | | | | 3.54 | 0.95 |
| Useless – Useful | 0.76 | | | | 3.71 | 0.95 |
| Reliable – Unreliable (Removed) | – | | | | 3.26 | 1.01 |
| Time consuming – Time saving | 0.65 | | | | 3.67 | 0.92 |
| **Performance expectancy** | | | | 0.88 | | |
| On a scale of 1–5 (1 = Strongly disagree, 5 = Strongly agree), to what extent do you agree or disagree with the following statements? | | | | | | |
| The use of autonomous passenger drones will help to get things done more quickly. | | | | | 3.66 | 0.79 |
| The use of autonomous passenger drones will increase productivity. | | | | | 3.66 | 0.80 |
| The use of autonomous passenger drones will increase the chance of achieving things that are important. | | | | | 3.60 | 0.79 |
| **Effort expectancy** | | | | 0.89 | | |
| On a scale of 1–5 (1 = Strongly disagree, 5 = Strongly agree), to what extent do you agree or disagree with the following statements? | | | | | | |
| My interaction/ communication with autonomous passenger drones will be clear and understandable for me. | | | | | 3.42 | 0.80 |
| I will find autonomous passenger drones easy to use. | | | | | 3.37 | 0.83 |
| For me, the use of autonomous passenger drones will be easy to learn. | | | | | 3.40 | 0.84 |
| With autonomous passenger drones, it will be easy to do what I want to do. | | | | | 3.40 | 0.85 |
| **Social influence** | | | | 0.91 | | |
| On a scale of 1–5 (1 = Strongly disagree, 5 = Strongly agree), to what extent do you agree or disagree with the following statements? | | | | | | |
| People who influence my behavior will think that I should use autonomous passenger drones. | | | | | 3.18 | 0.90 |
| People who are important to me will think that I should use autonomous passenger drones. | | | | | 3.17 | 0.92 |
| People whose opinions that I value will prefer to use autonomous passenger drones. | | | | | 3.23 | 0.93 |

**Table 1** (*continued*)

| Instrument items | *Factors* | *CR* | *AVE* | *α* | *M* | *SD* |
|---|---|---|---|---|---|---|
| **Price value** | | | | 0.88 | | |
| On a scale of 1–5 (1 = Strongly disagree, 5 = Strongly agree), to what extent do you agree or disagree with the following statements? | | | | | | |
| Autonomous passenger drone services will be a good value for money. | | | | | 3.32 | 0.86 |
| Autonomous passenger drone services will be reasonably priced. | | | | | 3.18 | 0.95 |
| Autonomous passenger drones will provide good value in terms of price. | | | | | 3.26 | 0.93 |
| **Facilitating conditions** | | | | 0.87 | | |
| On a scale of 1–5 (1 = Strongly disagree, 5 = Strongly agree), to what extent do you agree or disagree with the following statements? | | | | | | |
| I will have the resources I need to use autonomous passenger drones. | | | | | 3.22 | 0.89 |
| I will have access to relevant information on the use of autonomous passenger drones. | | | | | 3.25 | 0.86 |
| I can ask for support if I have difficulties in using autonomous passenger drones. | | | | | 3.46 | 0.87 |
| **Hedonic motivation** | | | | 0.92 | | |
| On a scale of 1–5 (1 = Strongly disagree, 5 = Strongly agree), to what extent do you agree or disagree with the following statements? | | | | | | |
| The use of autonomous passenger drones will be fun. | | | | | 3.56 | 0.84 |
| The use of autonomous passenger drones will give me pleasure. | | | | | 3.44 | 0.88 |
| The use of autonomous passenger drones will give me enjoyment. | | | | | 3.49 | 0.90 |
| I feel excited about using autonomous passenger drones. | | | | | 3.48 | 0.92 |
| **Habit** | | | | 0.88 | | |
| On a scale of 1–5 (1 = Strongly disagree, 5 = Strongly agree), to what extent do you agree or disagree with the following statements? | | | | | | |
| The use of autonomous passenger drones will become a habit for me. | | | | | 3.12 | 0.93 |
| I could use autonomous passenger drones. | | | | | 3.36 | 0.89 |
| Using autonomous passenger drones could become natural to me. | | | | | 3.29 | 0.93 |
| **Use intention** | | 0.91 | 0.77 | 0.91 | | |
| On a scale of 1–5 (1 = Strongly disagree, 5 = Strongly agree), to what extent do you agree or disagree with the following statements? | | | | | | |
| In the future, I intend to use autonomous passenger drones. | 0.85 | | | | 3.35 | 0.89 |
| In the future, I intend to use autonomous passenger drones on a regular basis. | 0.87 | | | | 3.17 | 0.96 |

(*continued on next page*)

**Table 1** (*continued*)

| Instrument items | *Factors* | *CR* | *AVE* | *α* | *M* | *SD* |
|---|---|---|---|---|---|---|
| I will recommend others to use autonomous passenger drones. | 0.90 | | | | 3.28 | 0.94 |

Note.
[a] The information that "engineers are experts who engage in programming and coding of the algorithms from its associated artificial intelligence (AI) system" was provided to respondents.

### 3.2. Hierarchal regression analyses

An ordinary least squares hierarchal regression analysis was conducted on SPSS 26.0. Consistent with prior studies (e.g., Ref. [60,61]), the constructs were entered into the regression model based on their assumed causal order. The regression model controlling for age, gender, ethnicity, prior drone use, education level, marital status, and household income was estimated to examine the predictive effects of news media attention, trust in AI system, trust in AI engineers, attitude, and various UTAUT2 constructs on the intention to use autonomous passenger drones. The results of the regression indicated that the predictors explained 73.76% of the variance, $F(18, 983) = 153.49$, $p < 0.001$. In the final model, there were significant main effects for several UTAUT2 constructs, including performance expectancy (β = 0.06, $p$ = 0.029), social influence (β = 0.10, $p < 0.001$), price value (β = 0.10, $p < 0.001$), hedonic motivation (β = 0.19, $p < 0.001$), and habit (β = 0.36, $p < 0.001$). In model 2, these UTAUT2 constructs alone accounted for 63.82% of variance in intention to use ($p < 0.001$). The extended constructs in model 3 including trust in system (β = 0.08, $p$ = 0.019), news media attention (β = 0.06, $p$ = 0.005), and attitude (β = 0.06, $p$ = 0.004) also had significant main effects on intention to use. These extended constructs accounted for 0.76% of variance ($p < 0.001$). Results are presented in Table 3.

### 3.3. Structural equation modeling for mediation analyses

The hypothesized mediation model was tested using structural equation modeling (SEM) on MPlus 8.3 [78]. Similar to the regression analyses, the SEM analysis included control variables of age, gender, ethnicity, prior drone use, education level, marital status, and household income. We performed 12 modifications in the measurement model by specifying error covariances (i.e., trust in system and trust in engineers; 8 within trust in AI system; 3 within trust in AI engineers; 1 within attitude). The measurement model showed good model fit: $\chi^2$/df = 2.74; CFI = 0.95; TLI = 0.95; RMSEA = 0.042, 90% CI = [0.040, 0.044]; SRMR = 0.04. The measurement model presented satisfactory composite reliability (CR), with all values exceeding 0.70, and acceptable average variances extracted (AVE), with all values exceeding 0.50 [79], except for attitude (i.e., 0.044). This is the result of setting the cut-off value for the factor loadings at 0.50, following established recommendations for studies with sample sizes larger than 200 [80]. Thus, we conclude that convergent validity was marginally achieved in our sample [81]. Further, as none of the AVE values were lower than the square of the correlation coefficients, we conclude that discriminant validity was achieved in our sample [81]. We performed 2 additional modifications in the structural model by specifying error covariances (i.e., 1 within trust in AI system; 1 within news media attention). The structural model showed good model fit: $\chi^2$/df = 2.39; CFI = 0.95; TLI = 0.95; RMSEA = 0.037, 90% CI = [0.035, 0.039]; SRMR = 0.037. The structural model accounted for 63.00% of the variance in use intention. All paths were positively significant except for the relationships between news media attention and attitude ($p$ = 0.675), as well as between trust in engineers and intention to use ($p$ = 0.219). Subsequently, mediation effects were tested using the bootstrap method to estimate standard erros with 1,000 bootstrap samples. More concretely, the indirect effect between trust in AI system and use intention through attitude accounted for 11.11% of the total effect ($B$ = 0.08, β = 0.05, 95% CI [0.004, 0.092], $p$ = 0.028 ; whereas the indirect effect between trust in AI engineers and

**Table 3**
Ordinary least squares hierarchical regression model for factors predicting intention to use autonomous passenger drones.

| Variables | Model 1 (β) | Model 2 (β) | Model 3 (β) |
|---|---|---|---|
| **Block 1: Demographics** | | | |
| Gender | −0.08** | 0.01 | 0.01 |
| Age | −0.06 | −0.02 | −0.02 |
| Ethnicity | −0.04 | −0.002 | −0.01 |
| Prior drone use (i.e., civilian leisure drones) | −0.18*** | −0.03 | −0.02 |
| Education level | 0.05 | 0.05** | 0.05* |
| Marital status | 0.08* | 0.03 | 0.03 |
| Household income | 0.13*** | 0.01 | −0.002 |
| Incremental $R^2$ (%) | 9.18*** | | |
| **Block 2: UTAUT2 constructs** | | | |
| Performance expectancy | | 0.10*** | 0.06* |
| Effort expectancy | | 0.02 | −0.01 |
| Social influence | | 0.11*** | 0.10*** |
| Price value | | 0.12*** | 0.10*** |
| Facilitating conditions | | 0.06 | 0.04 |
| Hedonic motivation | | 0.21*** | 0.19*** |
| Habit | | 0.37*** | 0.36*** |
| Incremental $R^2$ (%) | | 63.82*** | |
| **Block 3: Extended constructs** | | | |
| News media attention | | | 0.06** |
| Trust in AI system | | | 0.08* |
| Trust in AI engineers | | | −0.01 |
| Attitude | | | 0.06** |
| Incremental $R^2$ (%) | | | 0.76*** |
| Total $R^2$ (%) | | | 73.76*** |

*Note.* $N$ = 1002.
*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

**Table 2**
Zero-order correlation matrix of study variables.

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. News media attention | – | | | | | | | | | | | |
| 2. Trust in AI system | 0.53*** | – | | | | | | | | | | |
| 3. Trust in AI engineers | 0.51*** | 0.80*** | – | | | | | | | | | |
| 4. Attitude | 0.34*** | 0.55*** | 0.55*** | – | | | | | | | | |
| 5. Performance expectancy | 0.40*** | 0.64*** | 0.66*** | 0.60*** | – | | | | | | | |
| 6. Effort expectancy | 0.52*** | 0.71*** | 0.70*** | 0.53*** | 0.70*** | – | | | | | | |
| 7. Social influence | 0.52*** | 0.61*** | 0.57*** | 0.38*** | 0.51*** | 0.66*** | – | | | | | |
| 8. Price value | 0.50*** | 0.65*** | 0.63*** | 0.44*** | 0.57*** | 0.68*** | 0.65*** | – | | | | |
| 9. Facilitating conditions | 0.51*** | 0.67*** | 0.64*** | 0.46*** | 0.56*** | 0.74*** | 0.67*** | 0.72*** | – | | | |
| 10. Hedonic motivation | 0.47*** | 0.68*** | 0.66*** | 0.56*** | 0.66*** | 0.73*** | 0.61*** | 0.63*** | 0.66*** | – | | |
| 11. Habit | 0.53*** | 0.66*** | 0.60*** | 0.50*** | 0.58*** | 0.73*** | 0.72*** | 0.71*** | 0.73*** | 0.75*** | – | |
| 12. Use intention | 0.54*** | 0.68*** | 0.63*** | 0.54*** | 0.61*** | 0.71*** | 0.69*** | 0.69*** | 0.69*** | 0.75*** | 0.81*** | – |

Note. ***$p < 0.001$.

use intention through attitude accounted for 51.83% of the total effect ($B = 0.14$, $\beta = 0.09$, 95% CI [0.033, 0.158], $p = 0.008$. Results are presented in Fig. 2.

### 3.4. Importance performance map analysis for structural model

Further, an importance performance map analysis (IPMA; [82]) was conducted on SmartPLS 4.1 [83] to evaluate the relative importance of constructs in the structural model. The IPMA is an extension to structural equation modelling analyses as it provides further information on the measurement quality (i.e., performance) and relative predictive power (i.e., importance) of all exogenous variables in the structural model. Results revealed that all four constructs performed well in terms of measurement quality. As for relative importance, trust in AI system carried the most weight, followed by news media attention, trust in engineers, and attitude, in this order. Results are presented in Fig. 3.

## 4. Discussion

The present study examined the effects of news media attention, trust in AI system, trust in AI engineers, and attitude under the UTAUT2 framework in the context of the AI application of autonomous passenger drones. We extended the UTAUT2 model by demonstrating that news media attention, trust in AI system, and attitude presented robust predictive values when UTAUT2 variables were present. Furthermore, we examined the relationships between the extended variables, namely news media attention, trust in AI system, trust in AI engineers, attitude, and behavioral intention. The results for the mediation analyses between news media attention and attitude through both trust constructs were consistent with a full mediation effect. Subsequently, the results for the mediation analyses between trust in AI system and use intention through attitude were consistent with a full mediation effect, whereas the results between trust in AI engineers and use intention through attitude were consistent with a partial mediation effect.

Our most important contribution is the finding that trust in engineers appears to be a forgotten dimension of trust in AI. When trust in AI was conceptualized, there had been the assumption that it alluded only to trust in the system. Indeed, this view was not entirely incorrect. Our regression model showed that the direct effect of trust in engineers disappeared when trust in system presented a significant effect on behavioral intention. This suggests that trust in the system itself possibly represents the trust in AI construct better than trust in AI engineers. Nevertheless, the SEM analysis showed that trust in AI was not a single-dimension construct in that trust in engineers had an indirect effect on behavioral intention through attitude. It is noteworthy that news media attention influenced trust in engineers just as strongly as trust in system. Taken together, they suggest that trust in engineers play a significant, albeit indirect, role in predicting the adoption of the technology. The effect of trust in engineers could become more salient in future when algorithmic biases and the role of AI engineers receive more news media reporting and thereby public attention, especially when AI applications present errors. At present, the predictive value of trust in engineers should not be ignored. Future studies should examine its predictive value in the presence of the trust in system dimension in other AI applications.

Notably, this study shows that news media can shape public perceptions toward the emerging technology of AI. News media attention was a robust predictor presenting direct effects on behavioral intention in both the regression model and the SEM. This is consistent with previous news media effect studies on support for general science and technology [84], and AI technology in general [85], as well as specific applications such as biotechnology [64], nanotechnology [86], and autonomous vehicles [60]. Indeed, when technologies are yet to be deployed in the public sphere, news media offers the main and, in many instances, the only source of information for members of the public. Supporting this view, initial learned trust in the model for trust in automated systems [87] was argued to be influenced by expectations and reputation of the brand before engaging in the technology. News media serves this purpose well because it is the default and primary source of information before deployment. Trust was shown in our study to be positioned not only as a factor influencing behavioral intention, but also as a mediator between news media attention, the affective state of attitude, and behavioral intention.

Naturally, the positive relationship between news media attention and trust as well as behavioral intention require that news media reporting to be positive in nature. Should the reporting be predominantly negative on the technology, there is no reason to expect members of the public to form a favorable attitude and thereby trust. Indeed, the news media landscape of Singapore presents a generally positive and neutral reporting style, in an effort to promote desirable values that the government deems appropriate and to take up a "nation-building" role [69]. This effort requires the censorships and reporting guidelines that regulate news media which often results in the avoidance of negative reporting. In this sense, members of the public generally received information and a sense of appreciation toward the advancement of technology whenever it gets reported.

Equally important was the significant relationship between attitude and behavioral intention. Indeed, the main effect of attitude remained

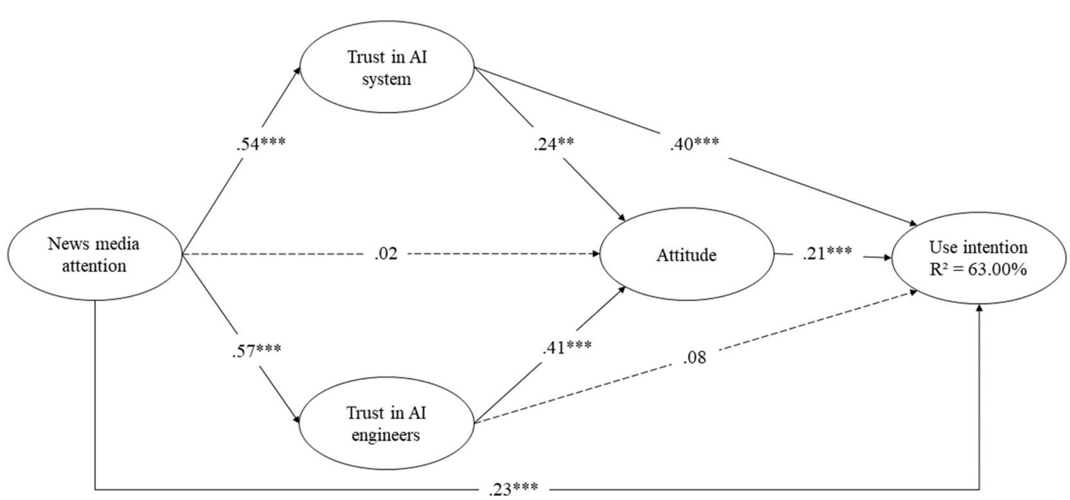


**Fig. 2.** *Structural Model of Mediation Analyses with Standardized Estimate. Note.* Controlled for gender, age, ethnicity, prior drone use, education level, marital status, and household income. Dotted lines denote nonsignificant paths. ***$p < 0.001$, **$p < .01$.

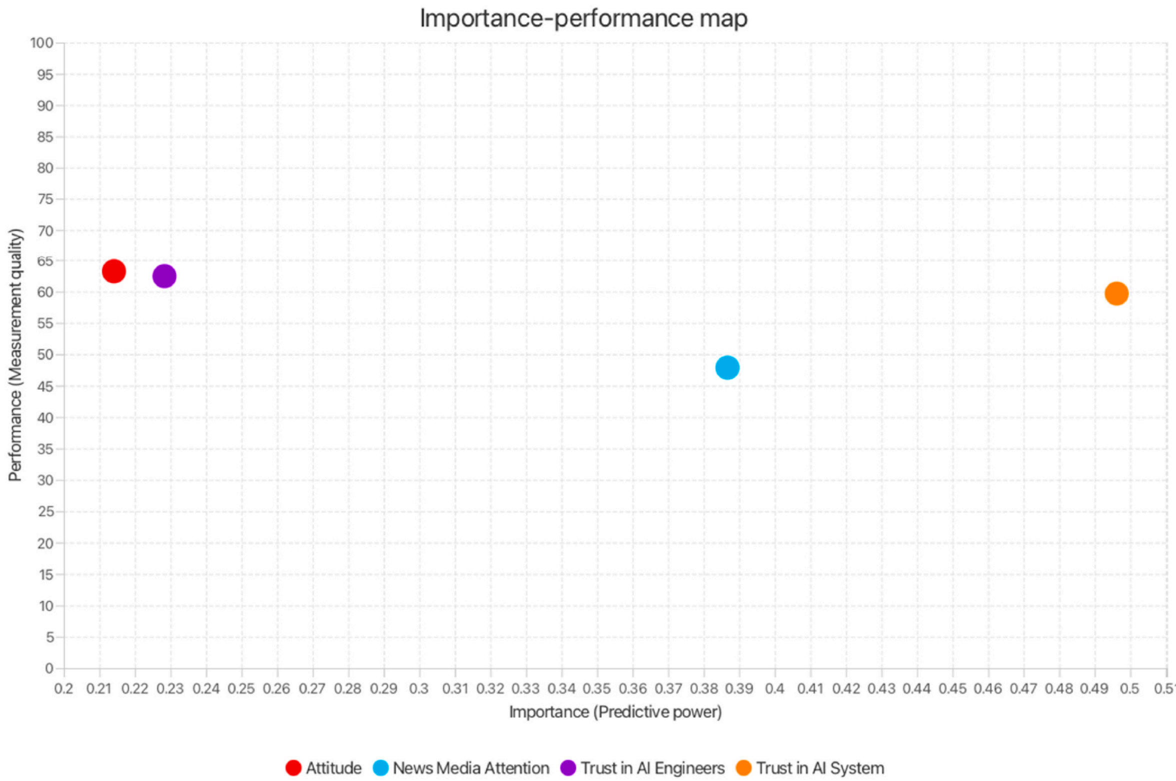


**Fig. 3.** Importance performance map analysis of variables in the structural model.

even in the presence of UTAUT2 constructs as well as the extended variables. This goes against the assumption of the UTAUT model where attitude was conceptualized as a mediator between various main constructs and use intention. Indeed, the conceptualization of attitude as a mediator is not wrong, as we showed its mediating role between trusts and use intention in the SEM. However, our results provided support that it may be necessary to include attitude as one of the direct predictors in the UTAUT2 framework for emerging technologies that are not widely accessible among the public. Whereas some studies have attempted to address this issue by excluding certain variables from the model, we argue that this may be unnecessary, or at the least, insufficient. The inclusion of attitude may capture public perceptions toward emerging technologies more accurately before deployment, a time when the public is not entitled with the necessary information to form perceptions along the lines of UTAUT2 constructs. This inclusion may be particularly useful for public perception studies. Future UTAUT2 studies on emerging technologies should consider the necessity of this inclusion.

The UTAUT2 constructs presented revelatory findings on the current state of public perceptions. More concretely, the non-significant effects of effort expectancy and facilitating conditions were not unexpected for a technology yet to be out in deployment. Members of the public has not directly observed autonomous passenger drones in practice and have no expectations on what the technology requires and affords. However, significant effects of performance expectancy, price value, and hedonic motivation on behavioral intention suggest that the public may have some idea about what the technology may offer to them and how much they expect to pay as a user. Similarly, the significant effect of social influence also suggests that people seemed to understand what the social climate would be like when the technology is in deployment in the future. This finding somewhat contradicts previous empirical evidence where some UTAUT2 constructs presented nonsignificant relationships with behavioral intention in emerging technologies. For example, price value for augmented reality [28]; and effort expectancy for autonomous vehicle [72]. Thus, these assessments may turn out to be inaccurate, but this imagination of social climate was nonetheless predictive at present. Finally, that habit was the most robust predictor and yet reporting the second lowest mean was compelling, because it suggested that the user base for autonomous passenger drones may be loyal, even though it may be small in practice.

All in all, our findings entail several implications. First, we demonstrated the importance of distinguishing between trust placed in the AI system and engineers as they exerted influence on behavioral intention differently. More importantly, our results suggested that when introducing new AI applications, policymakers can leverage on positive news media reporting as the key means to shape public perceptions and thereby use intention. Particularly, they may want to focus on aspects that have the most influence on support for the technology. Second, we have demonstrated the necessity to include attitude in the main model of UTAUT2 in examining emerging technologies. This will be important for future studies as technological innovations such as AI and its subdisciplines such as deep learning gain momentum. Importantly, we demonstrated the robustness of the predictive power of trust in AI system and trust in AI engineers. Strategic communication on these issues would be essential for public support. At the current stage, such communication should focus primarily on trust in the system as the IPMA analysis revealed that the construct carried more weight in terms of use intention. However, as the emerging technology is integrated in the society, end users can interact with the system directly, thus instead forming the perception of trust through that interaction. We speculate the predictive power of trust in AI engineers may then enhance significantly, at which point strategic communication should follow accordingly.

The present study is not without limitations. First, it may be premature to study public perceptions of autonomous passenger drones using the UTAUT2 framework. As members of the public have low knowledge levels of the technology, they may have resorted to their imagination in responding to the survey. Some perception studies may have responded to this issue by removing constructs. We have addressed this by the inclusion of attitude. Future studies should consider qualitative methods which are deemed to be more comprehensive in gauging public perceptions in the early stage of technological development. Second, the use of online surveys precluded some individuals from participating in the research. For example, older adults who are not technologically savvy and who are equally impacted by the introduction of autonomous passenger drones in the urban area may be excluded. Finally, we conducted the public survey in Singapore, a country that has plans to introduce passenger drones in the near future. Furthermore, the Singaporean media landscape is also distinctive to other countries. This may potentially limit the generalizability of our findings to other geographical locations as the public may not have been exposed to such news media reporting.

## 5. Conclusion

We demonstrated empirically that trust in AI can be seen separately in terms of trust in AI system and trust in AI engineers, despite the latter's nonsignificant direct effects. We also demonstrated the necessity of including attitude in the main UTAUT2 model in the study context of emerging technologies whose information remain out of reach to the public. We presented the relationships between these extended variables and news media attention, showing news media effects on trust, attitude, and thereby use intention. In this study, we extended the UTAUT2 model with news media attention, trust in AI, and attitude constructs in gauging public perceptions toward the emerging AI technology of autonomous passenger drones.

## CRediT authorship contribution statement

**Shirley S. Ho:** Conceptualization, Funding acquisition, Supervision, Writing – review & editing. **Justin C. Cheung:** Conceptualization, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing.

## Declaration of interest statement

The authors have no conflicts of interest to declare.

## Acknowledgements

This research is supported by the National Research Foundation, Prime Minister's Office, Singapore under its Campus for Research Excellence and Technological Enterprise (CREATE) programme.

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