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Designing for Trust: How Human-Machine Interface Can Shape the Future of Urban Air Mobility

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ABSTRACT

This study investigates the influence of human-machine interface (HMI) design on passenger trust in autonomous electric vertical take-off and landing (eVTOL) vehicles. An immersive simulator-based experiment was conducted with 34 participants, exposing them to four HMI conditions: baseline, movement, hazard detection, and full information condition. As related measures of passenger trust, we collected self-reported measures including trust, perceived safety, perceived reliability, and intention to use. In addition, physiological measures including gaze behavior, electrodermal activity, and heart rate were collected. The results indicated that movement and hazard detection information improved passenger trust, suggesting that HMI design could play a crucial role in enhancing the acceptance of autonomous eVTOLs. In addition, gaze behavior showed a stronger relationship with self-reported trust than other physiological measures. The findings underscore the importance of HMI design in fostering passenger trust, which is critical to the success of urban air mobility.

KEYWORDS

Urban air mobility (UAM); electric vertical take-off and landing (eVTOL) vehicle; passenger trust; human-machine interface design; physiological measure

1. Introduction

Urban air mobility (UAM) is a concept that envisions a safe, efficient, accessible and quite air transportation system for passenger mobility, cargo delivery, and emergency management within or traversing metropolitan areas (Cohen & Shaheen, 2021). The concept of UAM services is not new, as there already exist air transportation methods around urban areas using vertical take-off and landing aircraft such as helicopters (Garrow et al., 2021). However, advance in battery, distributed electric propulsion, and autonomy technologies has fostered the development of novel category of aircraft known as electric vertical take-off and landing (eVTOL) vehicles, which has recently increased interest in UAM (Garrow et al., 2021).

Based on the UAM maturity levels, it is anticipated that eVTOLs will transition from initially piloted environments to remotely operated or fully automated configurations in the long term (Goodrich & Theodore, 2021). In the initial stages (UAM maturity levels 1 and 2), onboard pilots are expected for each eVTOL to ensure operational safety. However, in the long term (above UAM maturity level 4), eVTOLs are expected to operate without an onboard pilot. They will transition to remotely operated vehicles controlled from the ground, eventually reaching a stage where real-time human intervention becomes unnecessary (Goodrich & Theodore, 2021). Transitioning from on-board pilots to a remotely operated environment reduces human-to-aircraft ratios, enabling fewer individuals to operate more aircraft and thereby reducing service costs (Chancey & Politowicz, 2020; Goyal et al., 2018).

Despite the potential benefits, implementing automated cockpit systems in eVTOLs can create distrust and discomfort among passengers. People tend to be hesitant to board aircraft without human pilots, questioning the safety and reliability of autonomous flight (Hughes et al., 2009; Mehta et al., 2017; Mühl et al., 2020). Passengers prefer to fly in piloted eVTOLs over remotely operated or fully automated aircraft (Shaheen et al., 2018). Therefore, to successfully integrate this technology into urban transport, it is important that passengers trust autonomous flights.

Current research in UAM primarily concentrates on the development of eVTOL vehicles (Straubinger et al., 2020). Despite the importance of building passenger trust for the acceptance of UAM, there is a lack of research in this area (Al Haddad et al., 2020; Kim et al., 2023). However, insights from other automation domains, like autonomous vehicles, can be applied to understand the factors influencing passenger trust in autonomous eVTOLs. Previous studies have indicated that passengers' trust in autonomous vehicles can be influenced by the design of the human-machine interface (HMI), which provides visual information about the vehicle's surroundings, including displaying the vehicle's future path or highlighting hazards (e.g., Haeuslschmid et al., 2017; Oliveira et al., 2020).

The aim of this study is to understand passenger trust in autonomous eVTOLs and enhance this trust through HMI design. To achieve this objective, we conducted a comprehensive literature review and a user study to explore the

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relationship between HMI design and passenger trust. The literature review delved into the concept of passenger trust, including its physiological measures, and examined the impact of HMI design on passenger trust. In the user study, the HMI visualized two types of information: movement information displaying the eVTOL's path and future behavior, and hazard detection information visualizing other aerial vehicles around the eVTOL. The contribution of this study is significant as it will provide insights into passenger trust based on the experiences in an immersive flight simulation environment. The results of this study can be used to design the HMI for eVTOLs to enhance passenger trust and acceptance of UAM. This study adds to the expanding body of research within the field of UAM and stands as one of the initial endeavors to explore the eVTOL passenger experience in simulated environments.

2. Literature review and hypotheses

2.1. Passenger trust in autonomous eVTOLs

Trust is a critical factor when it comes to acceptance of automated systems, such as passengers who will fly in autonomous eVTOLs (Hoff & Bashir, 2015; Kim et al., 2023). Trust is generally defined as the belief or expectation that a person or a system will perform as intended, reliably and accurately, and in the best interest of the operator (Muir, 1994). As trust occurs when the trustor delegates authority to the trustee despite the risks of failure, it is often considered a key factor in determining user acceptance and adoption of automation systems (Ghazizadeh et al., 2012; Hoff & Bashir, 2015). Several results have shown that passenger trust is important for UAM acceptance (Al Haddad et al., 2020; Kim et al., 2023). Al Haddad et al. (2020) conducted a stated-preference survey to identify relevant factors for the adoption of UAM. Results from a multinominal logit model showed that safety and trust, affinity to automation, data concerns, and socio-demographic factors are important considerations for potential users. Kim et al. (2023) also investigated user acceptance of UAM, with a focus on the trust factor. They extended the Technology Acceptance Model (TAM) developed by Davis (1989) with trust and transport service quality factors. The results revealed that trust in UAM is the most influential factor in its acceptance, even more than the perceived usefulness or ease of use.

The significance of trust in autonomous eVTOLs can also be inferred from the important role that user trust plays in the acceptance of autonomous vehicles (Chen, 2019; Choi & Ji, 2015; Hegner et al., 2019; Liu et al., 2019; Zhang et al., 2019, 2020). Several studies investigate the impact of trust in autonomous vehicle on the intention to use them based on the acceptance models such as TAM (Davis, 1989) and its extensions with trust factors (Ghazizadeh et al., 2012). In the TAM, the adoption of an information system is depicted through users' attitudes toward using the system and their intention to use it (Davis, 1989). In this context, attitude toward using refers to the extent of an individual's positive or negative evaluation of performing a behavior or using a specific technology system (Ajzen, 1991; Davis, 1989). Meanwhile, behavioral intention to use refers to the extent to which a person has consciously planned to either perform or abstain from a specified future behavior (Davis, 1989). Based on the TAM, Choi and Ji (2015) investigated the role of trust in a user's intention to use autonomous vehicles. They used a partial least squares model with survey data from 552 drivers, which showed that trust and perceived usefulness influence individual's intention to use an autonomous vehicle. This result is in line with the population in China, where initial trust in autonomous vehicles positively influence user's attitude toward using an automated vehicle, which in turn increase the intention to use them (Zhang et al., 2019, 2020). Chen (2019) investigated the influence of trust in autonomous shuttles on their acceptance in a scooter-dominant urban context. Although the results revealed that trust is not directly related to the intention to use autonomous shuttle services, trust was positively related to attitude toward using autonomous shuttle services, which is a strong antecedent of intention to use them (Ajzen, 1991; Davis, 1989).

Trust in autonomous eVTOLs may be influenced by passenger's perception (Kim et al., 2023). Considering that the trust in autonomous vehicles is related to the factors such as perceived reliability and safety (Vongvit et al., 2022), it can be inferred that these factors are also crucial in autonomous eVTOL environments. Reliability, which refers to the automation's ability to consistently perform task as the user expected (Mcknight et al., 2011), is closely related to one's trust in automation (Hoff and Bashir, 2015). In the autonomous vehicle domain, Kaur and Rampersad (2018) found that the reliability of driverless car is a significant predictor of trust. Beller et al. (2013) also showed that the faulty autonomous vehicle is less likely to be trusted compared to a more reliable one.

Passengers' trust in autonomous eVTOLs could be affected by their perceived safety as it is highly correlated to one's trust in autonomous vehicles (Nordhoff et al., 2021; Xu et al., 2018; Zhang et al., 2019). In UAM passenger contexts, perceived safety can be defined as a climate in which passengers could feel relaxed, safe, and comfortable during the flight (Xu et al., 2018). Zhang et al. (2020) revealed that perceived safety risk is a valid predictor of initial trust in autonomous vehicles. In an online questionnaire study conducted by Nordhoff et al. (2021), perceived safety was also served as a determinant of trust in partially automated vehicles. Xu et al. (2018) found a positive relationship between trust and perceived safety of automated vehicles, although they regarded perceived safety as a function of trust.

2.2. HMI design for promoting passenger trust

In this study, the impact of HMI design on two distinct types of information, namely movement and hazard detection, was investigated. The classification of this information was inspired by the categorization used for drivers of autonomous vehicles (Colley et al., 2022; Diels & Thompson, 2018; Koo et al., 2015). Previous research has highlighted that presenting such information can enhance the transparency of autonomous vehicles, leading to increased passenger trust (e.g., Oliveira et al., 2020).

Movement information refers to the information that visualize the future movement of autonomous eVTOLs such as ascending, descending, and turning. This information helps passengers anticipate and prepare for the movement of eVTOLs. Similar concepts were suggested by previous works, such as behavioral awareness information (Diels & Thompson, 2018), maneuver planning visualization (Colley et al., 2022) and "how" information (Koo et al., 2015). On the other hand, hazard detection information refers to the information that visualize surrounding elements to be detected and avoided before collision, such as other aircraft and birds. This information can let the passengers know that the automated system is always aware of its surroundings, and it can also let them know the reason behind certain actions like sudden turnings. Hazard detection information can be compared to situation awareness information (Diels & Thompson, 2018), scene detection visualization (Colley et al., 2022), and "why" information (Koo et al., 2015).

Previous studies have shown that presenting movement and hazard detection information through HMI can promote passenger trust in automated driving environments (Hartwich et al., 2021; Haeuslschmid et al., 2017; Oliveira et al., 2020). Hartwich and colleagues (2021) compared the effectiveness of different HMI versions (no HMI, context-adaptive HMI, and permanent HMI) in enhancing trust in autonomous vehicles. The permanent and context-adaptive HMIs presented the same information, including the visualization of other traffic and notifications of future behavior. The presence of an HMI was found to be associated with higher trust in autonomous vehicles, with no significant difference observed between the permanent and context-adaptive conditions. Haeuslschmid et al. (2017) also compared three HMIs (a chauffeur avatar, a graphical mini-world, and a traditional vehicle indicator) to examine their influence on trust and perceived safety of autonomous vehicles. Results showed that the graphical mini-world, which visualized the roads and intended behavior of the vehicle, led to greater trust than the traditional car indicator. Oliveira et al. (2020) similarly found that passengers placed more trust in highly automated vehicles with augmented reality displays that visualize intended vehicle behaviors and hazards in the environment.

Other studies have separately evaluated the effects of movement and hazard detection information on passenger trust (Colley et al., 2022; Löcken et al., 2020; von Sawitzky et al., 2019; Wintersberger et al., 2017). In a fixed-based simulator study, Löcken et al. (2020) investigated the impact of ambient light display on passenger trust. They examined three different conditions, including no display, conflict display, and conflict display with future trajectory information. The results showed significant differences in trust scores between the conditions, suggesting that displaying conflict information can increase passenger trust. Moreover, providing future trajectory information through ambient light display further enhances trust in automated systems. Wintersberger et al. (2017) evaluated the sole effects of traffic augmentation in automated driving systems. They found that visualizing traffic information, such as the heading of other vehicles and relative distance from the occupant's vehicle, increased passenger trust in autonomous vehicles. On the other hand, von Sawitzky et al. (2019) evaluated the effectiveness of movement information on passenger trust in fully automated driving. They found that displaying route indication information through augmented display systems, such as arrows and world-fixed displays, led to higher trust than the baseline condition. The preview HMI, which presented four seconds of future position of the vehicle based on the normal map, also led to higher trust ratings than the map HMI. However, inconsistent results were found in the online study by Colley et al. (2022). They investigated the effects of visualizing scene detection, scene prediction, and maneuver planning information on passenger trust in autonomous vehicles. The results showed that the scene detection and scene prediction information had no main effects on trust, and the maneuver trajectory information negatively affected trust. Based on the findings, we could hypothesize the following.

H1.1 The presentation of movement information positively affects passenger trust.

H1.2 The presentation of hazard detection information positively affects passenger trust.

2.3. Measuring trust with physiological responses

Physiological responses can provide valuable insight into assessing trust in automation, in addition to self-reported metrics. These measures can capture trust dynamics during human-automation interactions, making them a valuable tool for researchers studying trust (Kohn et al., 2021). These measures record biological responses such as gaze behavior, electrodermal activity, heart rate, neural measures, muscle responses, and respiration rate, which are gathered throughout the interaction and capable of capturing real-time changes in trust (Kohn et al., 2021; Rubagotti et al., 2022). In this study, gaze behavior, electrodermal activity, and heart rate related metrics were employed as objective measures of passenger trust.

2.3.1. Gaze behavior

Research has shown that passenger trust in automated systems, such as autonomous vehicles, can be inferred from their gaze behavior (Hergeth et al., 2016; Walker et al., 2019). To assess trust in automated driving, visual behaviors such as situation monitoring or involvement in other tasks have been used. Drivers who reported higher levels of trust in automation tended to monitor the road less closely than those with lower trust levels (Hergeth et al., 2016; Walker et al., 2019). Additionally, greater trust in automation has been positively associated with engagement in non-driving related tasks (Manchon et al., 2022).

Horizontal gaze dispersion, also known as horizontal gaze distribution, has been proposed as another measure of trust (Gold et al., 2015). Horizontal gaze dispersion, which is calculated by the deviation of gaze direction, is usually employed for the indication of driver's workload or cognitive demand (Du et al., 2020; Wang et al., 2014). However, Gold et al. (2015) argued that it could also be used as an indicator of trust, given that low gaze dispersion can be used as an indicator of mind wandering, in which the drivers are less involved in the scanning of the situation such as looking at the mirrors (He et al., 2011). Although the study by Gold et al. (2015) did not show a consistent correlation between trust and horizontal gaze dispersion for autonomous vehicles, Körber et al. (2018) could find that higher trust was related to the decreased horizontal gaze deviation. Combining with the results that people who have higher trust in autonomous vehicle revealed low monitoring behavior (Hergeth et al., 2016; Walker et al., 2019), there appears to be a correlation between trust levels and gaze dispersion: the lower the trust in autonomous eVTOLs, the more individuals are likely to concentrate on the flight scene, displaying scanning behavior. Conversely, higher trust in automation leads to less inclination to look around, resulting in lower horizontal gaze dispersion.

H2.1 Higher passenger trust is associated with increased task engagement and decreased horizontal gaze dispersion.

2.3.2. Electrodermal activity

Electrodermal activity (EDA) captures the skin conductivity that reflects sweat gland activation (Sharma et al., 2016). Sweat level is closely tied to sympathetic nervous system arousal and increases as the subject becomes more aroused. Therefore, EDA is widely used for a measure of trust, stress, surprise, and workload (Kohn et al., 2021). The time series of skin conductance can be decomposed into tonic and phasic components (Benedek & Kaernbach, 2010). The tonic component, known as skin conductance level (SCL), changes slowly during the interaction. The phasic component, or skin conductance response (SCR), changes rapidly in response to specific stimuli or events.

Research suggests that higher EDA responses are associated with low levels of trust. Walker et al. (2019) found that EDA and gaze behavior could serve as objective measures of trust in automated vehicles. They reported a strong correlation between the driver's EDA and trust, with higher self-reported trust associated with low EDA responses. Khawaji et al. (2015) found that EDA value is a valid measure of trust and cognitive load in text-chat environment. The findings indicated that higher value of EDA is correlated to the low trust level, especially in the case of low cognitive load.

H2.2 Higher passenger trust will be correlated to lower electrodermal activity.

2.3.3. Heart rate

Heart rate is also regarded as an indicator of an individual's arousal, including factors like stress and workload. As users' stress levels tend to decrease when interacting with automation they trust, heart rate has been used as a metric of trust (Kohn et al., 2021). *Heart rate change,* which is the difference between the baseline heart rate and the heart rate during an event, has been used as a measure of workload or trust in previous studies (Du et al., 2020; Waytz et al., 2014). For example, Waytz et al. (2014) hypothesized that individuals who trust autonomous vehicles will experience a lower increase in heart rate during an accident when the vehicle is in control. They assessed heart rate change by calculating the percentage change in beats per minute for 20 seconds immediately following the collision. Results showed that the change was smaller in the anthropomorphic condition, which had higher trust from drivers, than in the normal condition.

Heart rate variability measures the variation in time between each heartbeat, which is controlled by the sympathetic and parasympathetic nervous systems (Kohn et al., 2021). A lower heart rate variability is generally associated with a lower perceived level of safety and increased stress (Thayer et al., 2012). Sympathetic activation results in smaller variations between heartbeats in individuals who are stressed, while relaxed individuals show higher variation in each heartbeat. In combination with other physiological metrics such EDA, heart rate variability has been shown to be a reliable measure of interpersonal trust (Montague et al., 2014).

H2.3 Higher passenger trust will be correlated to lower heart rate change and higher heart rate variability.

3. Method

3.1. Participants

A priori power analysis was performed using G*Power version 3.1.9.7 (Faul et al., 2007) to establish the minimum sample size needed for testing the study hypothesis. The results showed that a sample size of twenty-four was required to achieve 80% power in detecting a medium effect, with a significance level set at $\alpha = 0.05$. We recruited thirty-four participants in their 20s or 30s from Yonsei University, representing potential future users of autonomous eVTOLs. Participation requirements were minimal, only excluding individuals who wore glasses, as glasses hindered the use of the head-mounted display. Among thirty-four participants, twelve were female and twenty-two were male, with a mean age of 27.7 years (SD = 4.37) and an age range of 20 to 38. More than half of participants (67.6%) reported that they were familiar with UAM through the media, while 32.4% reported having no prior knowledge of the concept. Prior to the experimental session, participants reported their initial trust in eVTOLs based on their pre-existing knowledge and the materials provided. Participants expressed slightly lower initial trust compared to a moderate level (M = 3.67, SD = 0.496). The analysis of physiological data only utilized data from 31 subjects due to technical issues. Data from 2 males and 1 female were excluded due to loss of gaze tracking, electrodermal activity or heart rate data. The experiment was approved by local Institutional Review Board (IRB) of Yonsei University. Participants received 20,000 won as compensation.

3.2. Apparatus

The fixed environment where the experiment was conducted was 1.4 m × 2.2 m in size, and the HTC Vive Pro Eye, an HMD-based virtual reality device, was used (Figure 1A). The device has a resolution of 1440 × 1600 pixels per eye and a maximum field of view of 110°. Eye tracking data was collected using the eye-tracking unit with a maximum frequency of 120 Hz and an accuracy range of 0.5°–1.1°. The Empatica E4 wristband was used to measure electrodermal activity and heart rate during the flight (Figure 1B). A motion simulator (GAMA Titan G6) was used to increase immersion of flight (Figure 1C). The motion simulator provides six degrees of freedom, including pitch, roll, yaw, heave, sway, and surge. All equipment was connected to a desktop computer with an Intel Core™ i7-8700K CPU at 3.70 GHz, graphics with NVIDIA GeForce GTX 1080Ti, and 16 GB of memory. The flight simulation was built using the Unity Engine.

3.3. Procedure

This study utilized a within-subjects design with two independent variables: presence of movement information and presence of hazard detection information. The participants were initially provided with a comprehensive description of the experiment and signed consent form to participate in the experiment. Participants then completed an initial survey on their age, gender, and initial trust level after they were provided the description on UAM. Then they were asked to move to the motion simulator and wearing the E4 wristband and VR headset.

The experimental session comprised four flights featuring different HMI types. The order of these conditions was partially counterbalanced using a balanced Latin square design to mitigate the impact of order effects. All flights had identical flight times, routes, surrounding traffic, and physical motion. Prior to the start of every flight, eye tracking calibration was checked to make sure the gaze behaviors are recorded accurately. Participants were given two instructions: (1) Place your non-dominant hand on your lap and minimize its movement during the flight, and (2) imagine you are in a real eVTOL, only watching the video at the center of the cockpit when you thought you would engage in a different task in a real autonomous flight (e.g., work, entertainment). The second instruction aimed to elicit natural gaze behavior from passengers; without it, participants might have solely looked out of the window during the flight. Tasks like answering questions about the video were intentionally not assigned to prevent participants from overly focusing on the video and deviating from their natural gaze behavior. After each flight, participants completed a survey and took a break of at least 3 minutes to prevent motion sickness. A post-experimental interview was conducted after the entire session. The experiment lasted approximately 70 minutes.

Figure 1. Experimental settings and apparatus. (A) Head-mounted display with eye-tracking (HTC VIVE Pro Eye). (B) Wristband with EDA and heart rate sensors (Empatica E4). (C) Motion simulator (GAMA Titan G6).

3.4. HMI design

The experimental design used in this study is a 2 × 2 within-subjects factorial design, with two independent variables: presence of movement information and presence of hazard detection information (Figure 2). All information was provided on the windshield. Movement information was presented visually through a 1-meter-wide path with a cyan color (Figure 2B). Hazard detection information was provided by detecting other eVTOLs within a specific boundary and displaying their location and distance (Figure 2C). The color of the square changed based on the relative distance and direction between eVTOL and detected aircraft. Each participant in the study was exposed to all four combinations of these two variables, with the full condition providing both movement and hazard detection information (Figure 2D), and the baseline condition providing no information (Figure 2A). Throughout the flight, a video of building blocks was played in the center of the cockpit.

3.5. Flight scenario

The flight scenario was developed based on the mission profile of Uber Elevate (UBER Elevate, 2018). The flight of the autonomous eVTOL was initiated from the roof of a 50 m tall building (point D in Figure 3). EVTOL hovered at 65 m for 20 seconds and then had two ascent sections, 200 m and 450 m. At 450 m, the eVTOL maintained cruising altitude for 150 seconds. The descent followed a reverse sequence, including a hover descent, first to 200 meters and back to the rooftop (point A in Figure 3). Each flight scenario lasted approximately 290 seconds, including an initial and final 20-second hover. The total length of the scenario was 7.8 km.

During the flight, there was one critical event in which an unauthorized helicopter was hovering on the eVTOL's

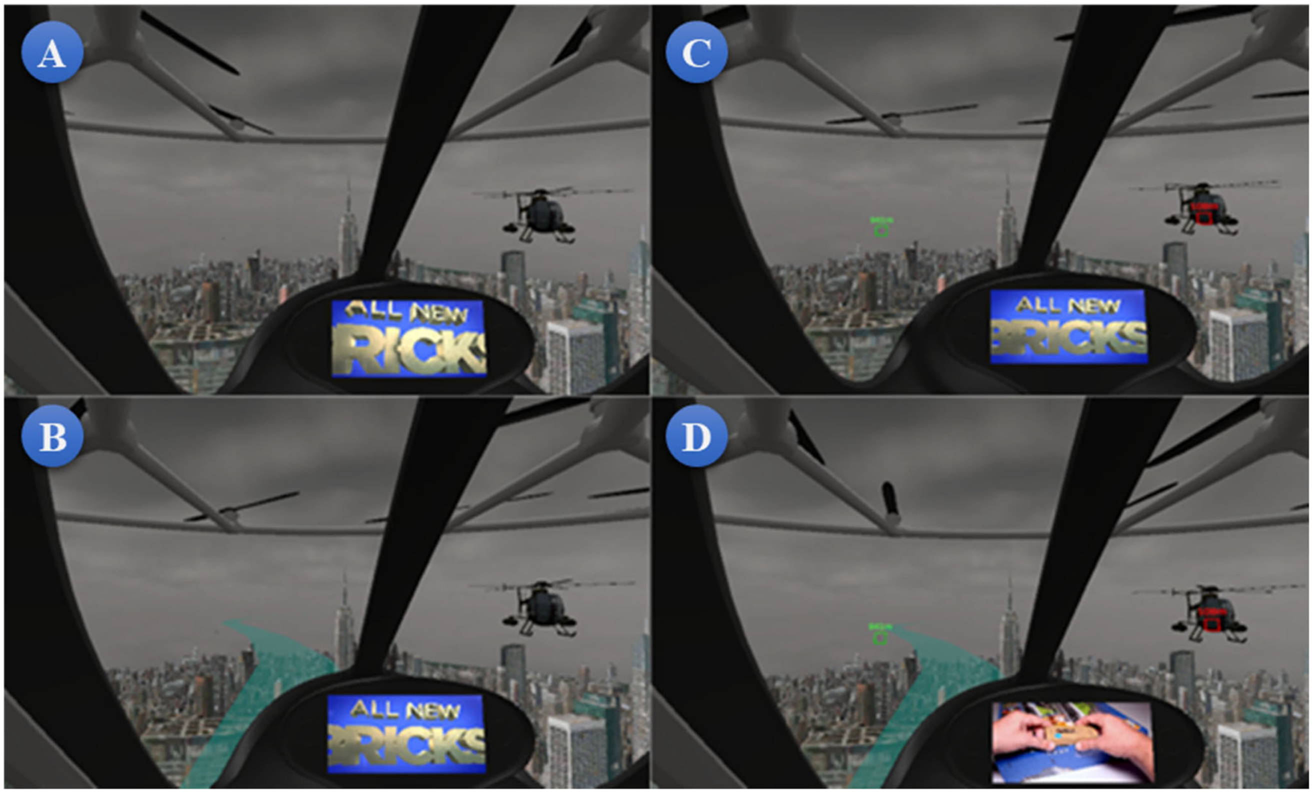

Figure 2. Snapshot of HMI conditions. (A) No HMI, (B) Movement HMI, (C) Hazard detection HMI, and (D) Full HMI.

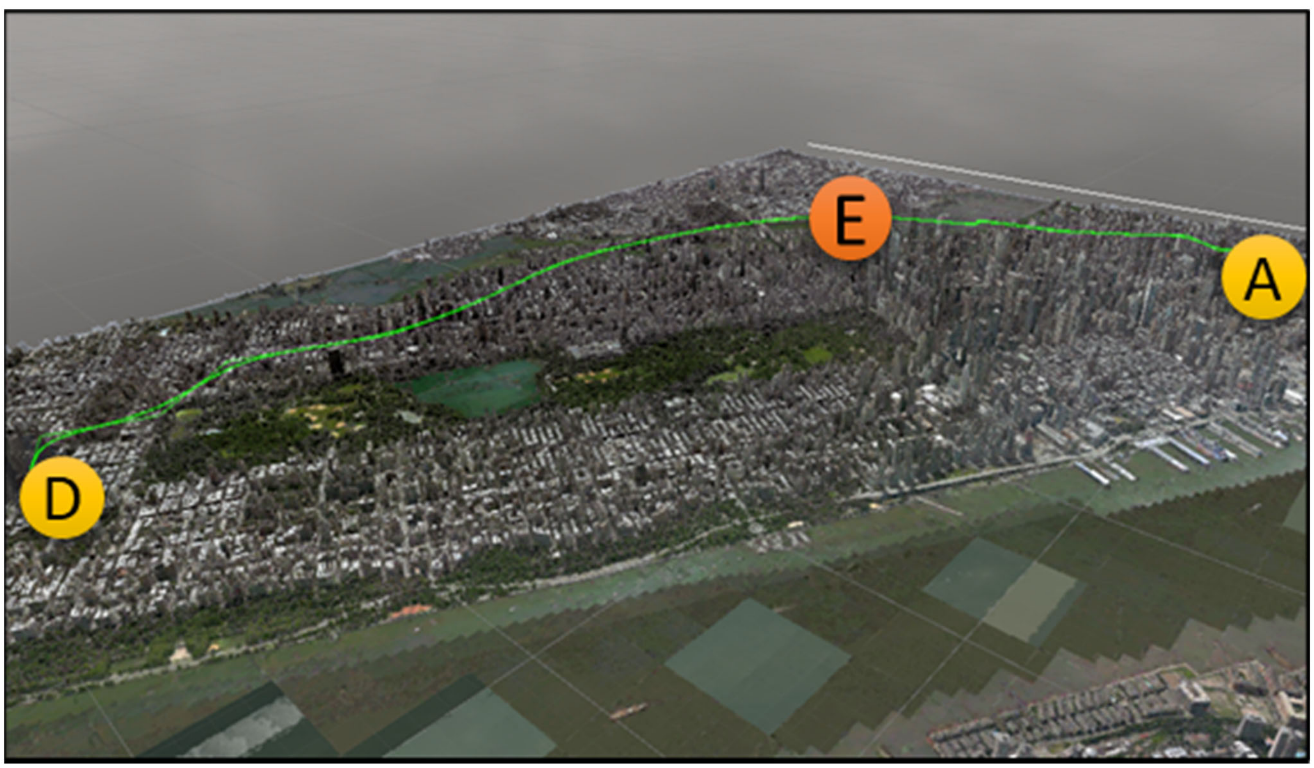

Figure 3. Snapshot of map and flight routes. Ⓓ indicates the departure point. Ⓔ indicates the avoidance event. Ⓐ indicates the arrival point.

path (Figure 2). When the distance between the two vehicles fell below 600 meters, a 1-second beep sound was emitted, and the eVTOL's route was altered to the left to avoid a potential collision. This event happened 170 seconds into the scenario (Point E in Figure 3).

3.6. Data collection and analysis

3.6.1. Self-reported questionnaire

We collected self-reported measures on trust in eVTOLs, perceived safety, perceived reliability, and intention to use

Table 1. Questionnaire items of self-reported measures.

Measure	Number	Questionnaire item
Trust in autonomous aerial vehicle (adapted from Jian et al., 2000)	T1	The eVTOL is dependable
	T2	The eVTOL is reliable
	T3	I can trust the eVTOL
	T4	I am confident in the eVTOL
	T5	The eVTOL provides security
	T6	The eVTOL has integrity
	T7+	The eVTOL is deceptive
	T8+	The eVTOL behaves in an underhanded manner
	T9+	I am suspicious of the eVTOL's intent, action, or outputs
	T10+	I am wary of the eVTOL
	T11+	The eVTOL 's action will have a harmful or injurious outcome
	T12	I am familiar with the eVTOL
Perceived reliability (adapted from Körber, 2018)	R1	The eVTOL is capable of interpreting situations correctly
	R2	The eVTOL works reliably
	R3+	The eVTOL malfunction is likely
	R4	The eVTOL is capable of taking over complicated tasks
	R5+	The eVTOL might make spradic errors
	R6	I am confident about the eVTOL 's capabilities
Perceived safety (adapted from Xu et al., 2018)	S1	I felt safe during the flight in the autonomous eVTOL
	S2	I felt relaxed during the flight in the autonomous eVTOL
	S3+	I felt risky during the flight in the autonomous eVTOL
Intention to use (adapted from Davis, 1989)	I1	I intend to use autonomous eVTOL in the future
	I2	I expect that I would use autonomous eVTOL in the future
	I3	I plan to use autonomous eVTOL in the future

Note: + indicates the inverse items.

(Table 1). In the experiment, participants were provided with questionnaire items translated into Korean. All self-reported measures were collected with 7-points Likert scale. The Cronbach's alpha test was conducted to evaluate the internal consistency of each variable, and the Shapiro-Wilk test was performed to check for normality of the self-reported measures.

A two-way repeated measures ANOVA was used to evaluate the effects of movement and hazard information on self-reported measures. Pairwise comparisons with multiple paired t-tests with a Bonferroni correction were conducted to assess statistical differences between conditions. We used a significance level of 0.05 for all conducted statistical tests. All statistical analysis was conducted by using IBM SPSS statistics 26.

3.6.2. Physiological responses

We gathered physiological data as well as self-reported trust to explore their correlation. Table 2 outlines the physiological measures employed in this study, including five trust-related measures of gaze behavior, electrodermal activity, and heart rate.

The participants' gaze data was obtained using Tobii XR SDK for Unity and SRanipal Runtime software (OpenXR). Tobii XR SDK uses a machine-learning algorithm called gaze-to-object mapping (G2OM) to predict if an object gets visual attention from the participant. The raw eye tracking data was collected at a fixed rate of 50 Hz and included system time, flight time, focused objects, gaze validity, and the unit vector of gaze direction relative to the eVTOL's heading direction. The eye tracking data was pre-processed by matching the system time with E4 server time and filtering out invalid gaze information. Gaze on display time was calculated by the proportion of time spent watching the video during flight. Horizontal gaze dispersion was computed by the standard deviation of gaze direction relative to the heading direction of eVTOL.

The raw data of electrodermal activity was obtained from the Empatica E4 manager software with 4 Hz of raw data frequency. Ledalab V3.4.9, a Matlab-based software for skin conductance data analysis, was used to process the collected raw data of electrodermal activity. The data was manually modified to remove artifacts such as sudden drops of skin conductance to zero. Continuous decomposition analysis was then conducted to separate the tonic and phasic parts of skin conductance. The time window of analysis was set during the whole flight. The phasic part of skin conductance, namely the skin conductance response, was used for analysis.

The heart rate data was also gathered from the Empatica E4 manager software, with raw inter-beat interval and averaged heart rate values computed in spans of 10 seconds. The inter-beat interval data was used to calculate heart rate variability during the flight by computing the standard deviation of inter-beat interval within the time window. Heart rate change was calculated by subtracting the averaged baseline heart rate from the averaged heart rate during flight.

As physiological responses have large variability among individuals, repeated measures correlation analysis was used to investigate the relationship between self-reported trust and physiological measurements (Bakdash & Marusich, 2017). The data was bootstrapped to obtain a 95% confidence interval. Friedman tests were conducted to assess the differences in physiological responses between conditions. Subsequently, a post hoc analysis was performed utilizing the Wilcoxon signed-rank test with Bonferroni correction to account for multiple comparisons.

3.6.3. Post experiment interview

Following the experimental sessions, a structured post-interview was conducted to evaluate the impact of HMI design

Table 2. Description on physiological response metrics.

Category	Variable	Unit	Description
Gaze behavior	Gaze on display time	Percentage	Percentage of time spent staring at a display during flight
	Horizontal gaze dispersion	Radian	Standard deviation of horizontal gaze direction
Electro-dermal activity	Skin conductance response	Micro-Siemens	Average phasic activation during flight
	Heart rate variability	Millisecond	Standard deviation of inter-beat-interval
Heart rate	Heart rate change	Beat per minute	Difference in average heart rate between cruising and avoidance

Table 3. Descriptive statistics of self-reported measures ($N = 34$).

Dependent variable	HMI condition	Mean	Std. deviation
Trust	None	3.94	1.146
	Hazard	4.56	1.030
	Movement	4.91	0.833
	Full	5.25	1.018
Perceived reliability	None	3.78	1.058
	Hazard	4.34	1.029
	Movement	4.46	0.917
	Full	4.98	1.017
Perceived safety	None	3.44	1.476
	Hazard	3.94	1.218
	Movement	4.75	1.212
	Full	4.87	1.295
Intention to use	None	4.03	1.430
	Hazard	4.52	1.272
	Movement	5.18	1.061
	Full	5.44	1.238

on trust (Table 3). Participants were asked to answer questions in the order of their HMI conditions, and their responses were recorded and transcribed for analysis. We utilized a conventional content analysis method to analyze the post-interview data. Towards the end of the interview, participants ranked their preferences, including the baseline. As the preference ranking data was collected as ordinal data, it was analyzed using a non-parametric Friedman test.

4. Results

4.1. Self-reported measures

Table 3 presents the findings of self-reported measures, rated on a seven-point Likert scale where four represents a neutral response. Participants indicated moderate levels of trust (M = 3.94, SD = 1.146) and intention to use autonomous eVTOLs (M = 4.03, SD = 1.430). However, their perceived reliability (M = 3.78, SD = 1.058) and perceived safety (M = 3.44, SD = 1.476) were slightly lower in the baseline condition, where no information was provided

The impact of movement and hazard detection information on trust was analyzed by two-way repeated measures ANOVA. The analysis of within-factors revealed that the main effects of movement ($F(1,2) = 23.964$, $p < 0.001$, $\eta_p^2 = 0.421$) and hazard detection ($F(1,2) = 8.609$, $p = 0.006$, $\eta_p^2 = 0.207$) were statistically significant. However, the findings indicated that there was no significant interaction between movement and hazard detection information ($F(1,2) = 1.565$, $p = 0.415$, $\eta_p^2 = 0.045$). These results indicate that each information contributes to the increase in passenger trust, with the effect size of movement information being larger than that of hazard detection information (Figure 4).

In order to examine the impact of movement and hazard detection information on perceived reliability, a two-way repeated measures ANOVA test was conducted. The analysis demonstrated significant main effects of movement ($F(1,2) = 17.603$, $p < 0.001$, $\eta_p^2 = 0.348$) and hazard detection information ($F(1,2) = 10.305$, $p = 0.003$, $\eta_p^2 = 0.238$) on perceived reliability. However, the interaction between the effects of movement and hazard detection information was found to be non-significant ($F(1,2) = 0.013$, $p = 0.865$, $\eta_p^2 = 0.001$).

In terms of perceived safety, the analysis indicated that there was a significant main effect of movement information ($F(1,2) = 19.769$, $p < 0.001$, $\eta_p^2 = 0.375$), while the main effect of hazard detection information was not significant ($F(1,2) = 2.084$, $p = 0.158$, $\eta_p^2 = 0.059$). There was no significant interaction effect between movement and hazard detection information ($F(1,2) = 1.740$, p =.196, $\eta_p^2 = 0.050$). These results imply that passengers' perceived safety is influenced only by movement information and is not affected by hazard detection information.

We examined the main and interaction effects of movement and hazard detection information on intention to use. The main effects for movement ($F(1,2) = 31.199$, $p < 0.001$, $\eta_p^2 = 0.486$) and hazard detection information ($F(1,2) = 4.945$, $p = 0.033$, $\eta_p^2 = 0.130$) were significant. The results indicated that the interaction effect between movement and hazard detection information was not statistically significant ($F(1,2) = 0.658$, $p = 0.423$, $\eta_p^2 = 0.020$).

A multiple linear regression analysis was performed using the stepwise selection method to examine the impact of perceived reliability and perceived safety on passenger trust in UAM (Table 4). The analysis showed that perceived reliability and perceived safety accounted for 76.0% of trust ($F = 209.326$, $p < 0.001$). The standardized beta coefficients of perceived reliability and perceived safety were 0.482 and 0.466, respectively, indicating that both factors had a positive influence on trust, and their effect sizes were comparable.

4.2. Physiological responses

A repeated measures correlation analysis was conducted to investigate the relationship between self-reported trust and physiological responses. We analysed gaze on display time, and horizontal gaze dispersion as gaze behavior of passengers. The results indicated that there is a positive correlation between trust and gaze on display time, which was in line with the hypothesis ($r_{rm} = 0.55$, 95% bootstrapped CI [0.417, 0.668], $p < 0.001$). Results showed that the type of HMI lead to statistically significant differences in gaze on display time (Friedman's Q(3) = 8.333, $p = 0.040$). Pairwise comparison revealed that participants looked at the display longer in full condition than hazard condition ($p = 0.047$) (Table 5).

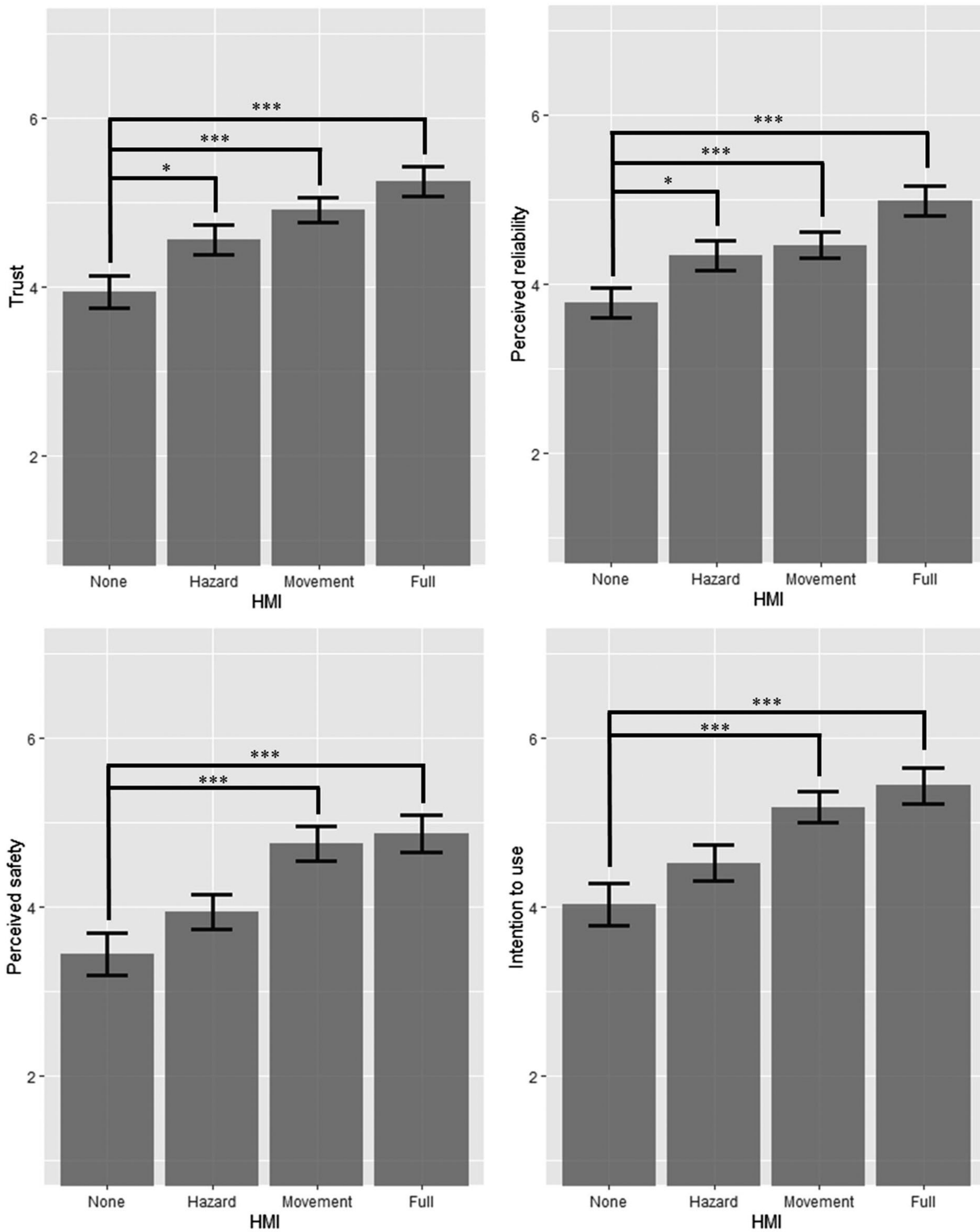

Figure 4. Self-reported measures according to the presence of movement and hazard detection information. *Note*: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table 4. Result of multiple linear regression on passenger trust.

Variable	B	SE	β	t	Sig.	Tolerance	VIF
Constant	0.960	0.197		4.887	<0.001		
Perceived reliability	0.490	0.060	0.482	8.206	<0.001	0.526	1.902
Perceived safety	0.365	0.046	0.466	7.941	<0.001	0.526	1.902
F				209.326***			
Adj. R^2				0.760			
Durbin-Watson				1.630			

Note: $***p < 0.001$.

The analysis found a significant negative correlation between passengers' trust and their horizontal gaze dispersions, with a repeated measures correlation coefficient of $r_{rm} = -0.39$ and a 95% bootstrapped confidence interval of [−0.541, −.220], indicating that as trust decreases, gaze dispersion increases. The Friedman test was also conducted to examine the differences in gaze dispersion across conditions during the flight, and the results showed significant differences (Friedman's $Q(3) = 12.019$, $p = 0.007$). Specifically, participants had greater gaze dispersion in the none ($p = 0.019$) or hazard condition ($p = 0.047$) compared to the movement condition.

The analysis showed no significant relationship between self-reported trust and skin conductance response ($r_{rm}(92) = -0.17$, 95% bootstrapped CI [−0.328, 0.008], $p = 0.098$), heart rate change ($r_{rm} = -0.07$, 95% bootstrapped CI [−0.273, 0.142], $p = 0.506$), and heart rate variability ($r_{rm} = 0.02$, 95% bootstrapped CI [−0.178, 0.206], $p = 0.862$). The Friedman test also did not show any significant difference in the skin conductance responses, heart rate change and heart rate variability across the HMI condition.

4.3. Post experiment interview

The results of the post-experiment interview regarding the positive and negative opinions on HMI designs are presented in Table 6. Results showed that participants generally found movement information beneficial, while they had conflicting opinions on the hazard detection information. Participants appreciated the predictability of eVTOL behaviors provided by the movement information.

> Having access to movement information makes me feel comfortable, as it allows me to predict the behavior of aircraft.

> If I were actually riding in a UAM, I would probably have a coffee or something to eat, and I think this direction would be really helpful.

However, some participants expressed that the movement information made them anxious, particularly during the descent phase, as the experience felt similar to riding a rollercoaster.

> It felt like I was riding a rollercoaster, but I wouldn't say I was excited. I was actually nervous about the possibility of falling.

Regarding the hazard detection information, positive responses focused on perceived reliability and situation awareness.

> I thought the aircraft was intelligent because it was able to identify and display other aircraft that were approaching.

> Compared to the baseline condition, providing hazard information is better because it informs the system's operating state.

In contrast, more than half of the comments about the hazard information were negative, citing issues such as distraction, lack of control, and aesthetic quality.

> I found it too distracting because the information kept changing constantly, and I couldn't focus on the video.

> I'm not sure why this information is necessary. After all, I don't have any control over the aircraft, do I?

Table 5. Repeated measures correlation analysis between self-reported trust and physiological measures.

	Trust	Gaze on display time	Horizontal gaze dispersion	Skin conductance response	Heart rate change	Heart rate variability
Trust		**0.55**	**−0.39**	−0.17	−0.07	0.02
Gaze on display time	**0.55**		**−0.48**	−0.06	−0.02	−0.05
Horizontal gaze dispersion	**−0.39**	**−0.48**		−0.08	−0.06	0.19
Skin conductance response	−0.17	−0.06	−0.08		−0.04	0.04
Heart rate change	−0.07	0.02	−0.06	−0.04		0.19
Heart rate variability	0.02	−0.05	0.19	0.04	0.19	

Note: All the bold values indicate a significance level of $p < .001$.

Table 6. Results of post experimental interview on HMI design.

Movement information			
Positive	Mentions	Negative	Mentions
Clear and predictable	26	Scary descent	7
Anxiety relief	17	Worried about helicopter	5
Situation awareness	9	Anxiety (like a roller coaster)	4
Familiarity	7		
Low monitoring	6		
Hazard detection information			
Positive	Mentions	Negative	Mentions
System status	18	Distraction and complexity	21
Situation awareness	12	Anxious and surprised	13
Confident in avoidance	8	Lack of control & useless	9
Relieve anxiety	6	Objects at a distance	8
Perceived intelligence	6	Difficult to understand	6
Full information			
Positive	Mentions	Negative	Mentions
Understanding on situation and behavior	14	Distraction and complexity	12
Confident in avoidance	12	Aesthetic quality	8
Selective attention	11		
Relieve anxiety	9		

Despite the lack of significant interaction effects between the movement and hazard information on self-reported trust, some participants acknowledged the potential benefits of combining the two types of information. The combined information made participants more confident in avoiding helicopter situations. However, the full HMI condition posed problems due to visual distractions that interfered with the sightseeing experience.

> … but with the movement and hazard detection information provided, I felt confident that the aircraft would avoid it.

> I found it better with the movement information because I knew where I was going, so I could focus my attention more selectively (as opposed to the hazard detection condition).

A Friedman test was conducted to assess the impact of HMI design on preference rank. The results indicated that there were significant differences in preference due to HMI design ($\chi 2(3) = 41.188$, $p < 0.001$). To further explore this, a post-hoc comparison was performed using the Wilcoxon signed-rank test with a Bonferroni-adjusted significance level of $p < 0.017$. The results showed that the full information was significantly preferable than the none ($Z = 4.006$, $p < 0.001$) and hazard detection information ($Z = 4.325$, $p < 0.001$). Similarly, the movement information was significantly preferable than the none ($Z = 3.983$, $p < 0.001$) and hazard detection information ($Z = 3.519$, $p < 0.001$). There were no significant differences were found between the full and movement information ($Z = 1.754$, $p = 0.079$) or between the hazard detection and none condition ($Z = 1.069$, $p = 0.285$).

5. Discussion

This study aimed to examine how HMI design impacted passenger trust in autonomous eVTOLs, utilizing a mixed-method approach with self-reported measures, physiological measures, and qualitative interview data. The experiment involved two types of information provided through the HMI: movement and hazard detection. The expectation was that both types of information would enhance trust, with the effects being influenced by perceived reliability and safety. The results suggest that utilizing HMIs to convey information can be a successful method for increasing passenger trust, but implementation in real-world design requires careful consideration.

The provision of movement information involved displaying the future path of eVTOLs, and it was found to significantly increase trust, as well as perceived safety and perceived reliability, which was in line with expectations. It allowed participants to anticipate the behavior of the eVTOL, prepare for it, and confirm that the UAM was functioning correctly. This information was presented in a non-intrusive manner, which helped to avoid distracting the passengers. As a result, providing movement information could be helpful in reducing the anxiety of early users and may continue to be effective even as autonomous flight becomes more commonplace, allowing passengers to prepare for the flight stage.

The hazard detection information was presented by showing the distance between the eVTOL and other aircraft. As expected, the hazard detection information also contributed to an increase in passenger trust. However, the provision of hazard detection information only resulted in an increase in perceived reliability of autonomous eVTOLs, without any noticeable changes in the perceived safety of passengers. This finding was unexpected, as hazard detection information could increase the perceived safety in highly automated driving situations (Colley et al., 2022). Passengers who received hazard detection information reported that the system was functioning correctly and that their comprehension of the flight situation had improved. However, excessive information proved burdensome and had the unintended consequence of distracting them. Furthermore, passengers' inability to influence the actions of the eVTOL made them feel that the information was unnecessary. Consequently, hazard detection information should be delivered in a less stimulating manner, and it would be more effective if passengers had some control over the situation, such as by having access to remote pilots.

Physiological trust measures included gaze behavior, electrodermal activity, and heart rate. Given that individual factors can greatly influence physiological measures, a repeated measures correlation was used for analysis. The study found a significant correlation between passengers' gaze behavior during the flight and their level of trust. Specifically, gaze on display time, which indicates engagement in non-monitoring tasks, was positively correlated with self-reported trust. These findings suggest that people may feel more comfortable engaging in personal tasks when they trust the eVTOL. This is consistent with previous research on highly automated driving environments, where drivers were more likely to engage in non-driving tasks when they trusted their vehicles (Manchon et al., 2022). Additionally, horizontal gaze dispersion, which represents active monitoring of the flight situation, was negatively correlated with trust. This suggests that people may seek information about their surroundings even when they have no control over the situation.

However, the electrodermal activity and heart rate did not exhibit a significant correlation with self-reported trust. One possible explanation for this finding is that the participants were not sufficiently stimulated by the flight scenario used in the study. Previous research that measured electrodermal activity and heart rate used scenarios that required participants to take control of the vehicle (e.g., Du et al., 2020) or involved emergency situations, such as crashes (Waytz et al., 2014). Although the avoidance situation in this scenario was high-risk, participants did not perceive it as urgent. Therefore, it is uncertain whether skin conductance and heart rate indicators can be considered reliable measurements in the UAM environment, and further research is needed.

This study has several limitations that should be addressed in future research. Firstly, while a counterbalanced experimental order can eliminate order effects, it cannot account for learning effects. Participants were able to predict eVTOL movements in avoidance situations after the initial exposure to the scenario, potentially reducing the impact on physiological measures such as heart rate changes. Therefore, future studies should explore passengers' physiological responses to unexpected events by creating longer and more varied flight scenarios. Secondly, trust in automation models describe two states: overtrust, where a user's trust exceeds system capabilities, leading to misuse, and distrust, where trust falls below system capabilities, resulting in disuse (Lee & See, 2004). When designing automation, it's essential to consider both states, calibrating individual's trust level with automation capabilities. In this study, our focus primarily concentrated on the distrust state, aiming to boost trust among potential UAM users. This decision was made because passengers will have no control over the flight situation, and there is research indicating that early users are likely to be less comfortable and have low trust in autonomous eVTOLs (Hughes et al., 2009; Mehta et al., 2017; Shaheen et al., 2018). However, when evaluating trust in eVTOLs from the viewpoint of pilots or operators, it becomes crucial to calibrate trust from both the overtrust and distrust states. Therefore, future studies should explore effective methods for calibrating trust comprehensively.

6. Conclusion

In this study, we explored the influence of HMI design on passenger trust in autonomous eVTOLs. Our aim was to optimize HMI to enhance trust and acceptance of automated aircraft in UAM. An immersive simulator-based experiment was conducted with 34 participants, exposing them to four HMI conditions: baseline, movement, hazard detection, and full information condition. Self-reported measures and physiological measures related to passenger trust were collected. The key findings revealed effects of HMI design such as movement and hazard detection information on passenger trust. In particular, this study revealed a substantial increase in passenger trust when movement and hazard detection information were provided. Additionally, we discovered a significant correlation between the passengers' gaze behavior and their trust levels, suggesting that gaze behavior could serve as a real-time measure of passenger trust. This study marks a pioneering effort in comprehending passenger trust and acceptance of autonomous eVTOLs for UAM. The results offer valuable insights for researchers and engineers aiming to promote the widespread adoption of UAM with autonomous eVTOLs.

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