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Trust and user acceptance of pilotless passenger aircraft

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ABSTRACT

This study examines the empirical relations between trust and society's willingness to accept an emerging technology in air travel. This paper extracts attitudinal factors related to trust from the Remotely Piloted Passenger Aircraft Attitude Scale. The analyses identified "trust in remotely piloted aircraft" and "trust in on-board pilot and aviation regulators", among other variables such as age, gender, and perceived risk, to influence aviation consumer's acceptance of a pilotless aircraft. The modelling reveals asymmetrical and diminishing effects of trust, where an incremental improvement in trust from the mean has a limited effect on acceptance, while the equivalent loss of trust from the mean significantly reduces acceptance. Moreover, trust in on-board pilot and regulators increases the probabilities of "very likely" and "very unlikely" acceptance at the expense of neutrality. While polarisation in acceptance is consistent with earlier findings in cognizant context, this study provides empirical insights on the dimensions of trust closely linked to such polarisation.

1. Introduction

Urban Air Mobility (UAM) refers to an urban transportation system that moves people by air instead of using road, rail or water transport modes. It has been promoted as a solution to alleviate congestion in cities. An example is Uber Elevate/Joby Aviation, which in its vision expects a fleet of quadcopters or variants with vertical take-off and landing capability in their hundreds to service congested cities based on an on-demand, shared system. A study prepared by Booz Allen Hamilton (BAH) (2018) for the National Aeronautics and Space Administration (NASA) presents a positive outlook - that the UAM market is worth $2.5 billion in the near term, and up to $500 billion in the long term. A fully autonomous commercial aircraft (i.e., an airliner drone) is now technologically feasible (Hancock, Nourbakhsh, & Stewart, 2019). However, in addition to weather, infrastructure, operational, legal, and regulatory hurdles in ensuring a safe UAM system, a constraint may be pilot supply.

Pilot licensing and certification requirements are a major obstacle for new technology such as UAM, which, if the typical new product development pathway was to be followed, may need to scale to drive down unit costs. However, scaling UAM will be extremely challenging if every flight requires a human pilot on-board. Indeed, pilot shortage has been identified as one of the main rationales for introducing pilotless or reduced or single pilot operations (see Nunes, 2019). Understanding user acceptance of remotely piloted passenger aircraft (RPPA) or pilotless passenger aircraft for passenger transportation is useful in determining the acceptability of UAM. This is particularly the case as remotely piloted aircraft can be a technology that enables the transition from the current aircraft configuration to a fully pilotless form (Ward et al., 2021). Arguably, remote pilot operator may require simplified vehicle operations compared to an on-board pilot in conventionally piloted aircraft, enabling greater potential for scaling.

From a human performance perspective, and specifically human error, pilotless aircraft offer promise. The National Academy of Sciences, Engineering and Medicine (United States) define autonomous aircraft as "an aircraft that does not *require* pilot intervention in the management of the flight." (National Research Council, 2014:12 italics in original text). Fully autonomous aerial vehicles are different to remotely piloted aircraft. The former is an unmanned aerial vehicle system that requires no input from an operator onboard, whereas the latter still requires a pilot, similar to a pilot on-board civil aircraft, except the pilot is located remotely at a ground station. However, there are shades of grey between these configurations. The remotely piloted aircraft may be fully autonomous but with a 'safety remote pilot'. Due to advancements in drone technology, it is possible to operate a passenger aircraft remotely

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(Hancock et al., 2019), though not accepted from a regulatory perspective. Thus, in addition to the potential safety benefits, the key economic advantage of the pilotless or/and remotely piloted design is scalability, namely a team of remote pilots may be able to operate/control multiple aircraft at once.

In an attempt to protect fare paying passengers against commercial changes that could have an adverse impact on safety, aviation governing bodies such as the Civil Aviation Safety Authority (CASA) in Australia require airlines to demonstrate comparable levels of safety between the proposed, and existing approved operations (Civil Aviation Safety Authority, 2015). Such a requirement should naturally extend to the introduction of unmanned and remotely piloted aircraft (beyond initial certification). However, convincing the aviation governing authorities is only one step in this process, as airlines need to sell the new technology to the end user, in this case a fare paying passenger (Molesworth & Koo, 2016). In this context, and as it is the case with cognizant technologies such as drones, public acceptance is crucial.

Research on societal barriers can provide insight into the factors preventing acceptance, as well as the potential impacts of such technology on deployment and production goals. It is the former that is of interest to the present research, though this is not unrelated to the latter. Understanding public acceptability can inform the design of UAM, as well as estimation of when the individuals will adopt UAM (Garrow, German, & Leonard, 2022). Moreover, in a related sector, research in the use of ground automated vehicles (AV) reveals the importance of understanding user acceptance to achieve the societal benefits forecasted (e.g., Shariff, Bonnefon, & Rahwan, 2017; Xu et al., 2018).

There is substantial grey literature on attitude towards pilotless aircraft; however, academic research into public opinion and attitudes towards pilotless aircraft or/and automated pilots has concentrated on issues related to trust in technical systems and safety (for example, please see Bennett and Vijaygopal (2021) for a review). Technology acceptance models articulate some of the known factors that affect users' acceptance of technology (Bekier & Molesworth, 2017; Bekier, Molesworth, & Williamson, 2011; Davis, Bagozzi, & Warshaw, 1989; Muir & Moray, 1996; Thompson & Bailey, 2000; Westrum, 1991; Wixom & Todd, 2005). Applied to pilotless aircraft, the model also supports the significance of trust in public acceptability of UAM (Haddad, Chaniotakis, Straubinger, Plotner, & Antoniou, 2020). According to Mayer, Davis, and Schoorman (1995), trust is a psychological construct, and is associated with relinquishing control of a situation to another person or object under the assumption that the situation will be executed safely and well. Trust can be viewed as a heuristic used to make complicated decisions (Siegrist, 2019). Numerous studies have identified lack of trust as a critical factor underlying the divisive controversies in technology management (Slovic, 1993).

Trust has multiple dimensions; for instance, it is possible for a user to accept a technology but not trust the industry or the institution (Siegrist, 2019). Trust in technology may differ from the trust in the innovating firms/institutions/people and their communications (Hengstler, Enkel and Duelli, 2016, Nelson & Gorichanaz, 2019). Remotely piloted aircraft technology requires a sophisticated and reliable data-link system to operate, and depending on the configuration of the aircraft, a pilot may be located on-board, and/or at a remote ground station. Therefore, users are likely to differentiate between trust in remotely piloted aircraft technology, trust in on-board pilot, and trust in a remotely located pilot (Molesworth & Koo, 2016). Thus, a study of public opinion requires an instrument with the capacity to dissect the various dimensions of trust to better identify the root of the public's concern/s.

One way this could be revealed is by understanding to whom the trust is associated with, for instance: is it the aircraft manufacturer (e.g., Boeing NeXt, Airbus), the service provider (e.g., Uber Elevate/Joby Aviation), the regulators (e.g., FAA, CASA), or the operator/s (e.g., pilot/s on-board or the remote pilot/s)? In addition, these dimensions of trust may differentially and non-linearly relate to acceptance. For instance, akin to the effect flight safety information has on consumer behaviour (Koo, Collins, Williamson, & Caponecchia, 2018), the effect of increased trust on acceptance may vary depending on how much trust already exists, and there may even be threshold levels of trust from which any loss of trust has a significant negative influence on acceptance, whereas levels above have a relatively small effect. Although such relation has been noted in general risk analysis literature (e.g., Siegrist, 2019; Slovic, 1993), to the best of the authors' knowledge, it is yet to be empirically demonstrated in the study of public attitude towards air transport automation.

Modelling these effects in the context of remotely piloted passenger aircraft (RPPA) can contribute towards the development of management strategies for presenting the RPPA, and more generally, pilotless aircraft, to the general public. Overall, such efforts can contribute towards the understanding of aviation consumer attitudes and perceptions, which can aid the design of UAM business models (Ward et al., 2021), implement appropriate and effective marketing and public sector communications strategies (Bennett & Vijaygopal, 2021), pre-emptively address public acceptance challenges such as through demonstration of regulatory safety standards and systems, and early engagement of interest groups Booz Allen Hamilton (2018).

Against this background, the present study aims to answer the following two questions.

1. What are the salient attitudinal factors relating to trust with remotely piloted passenger aircraft (RPPA)?
2. How do these factors relate to willingness-to-accept remotely piloted passenger aircraft (RPPA)?

As shown in Fig. 1, the output of (1) is used as inputs to (2).

2. Trust and public acceptance in remotely piloted and pilotless passenger aircraft

To the best of the author's knowledge, the earliest published study on public acceptability of pilotless air passenger transport is by MacSween-George (2003). The study concluded that, provided with adequate logical and emotional appeals, the public can be persuaded to accept the technology-. It was hypothesized that over time the infiltration of experiences and information (such as autonomous ground vehicles, drones, pilotless cargo transport) will increase acceptance of pilotless aircraft in uses such as commercial passenger transport. The study recommended future research to aim to understand what influences public opinion or attitude. In fact, Vance, Bird, and Tiffin (2019) reviewed four independent studies using different methodologies across a twelve-year span (2003–2015) and concludes the willingness to use a pilotless aircraft has increased over time in the U.S.

In many applications "attitudes are measured in an attempt to predict behavior and are the target of persuasive appeals in an effort to shape behavior." (Guyer & Fabrigar, 2015: 183). As mentioned previously, academic research into attitudes towards pilotless aircraft or/and automated pilots has concentrated on issues related to trust in technical systems and safety (Bennett & Vijaygopal, 2021; Hughes, Rice, Trafimow, & Clayton, 2009). Hughes et al. (2009) examined how study subjects' attitudes towards the pilot (human and auto) are linked to their confidence in the pilot, trust in the pilot, the extent to which they felt anxious about the flight, and the degree to which they felt the pilot could handle an emergency situation. They found increasing public acceptance of automated pilots means increasing positive feelings and trust because these are the core factors addressing common concerns involving confidence, anxiety and emergency of an automated flight altogether. They also found the processes used to judge the human pilot did not differ significantly from the processes used to judge an automated pilot.

The close association between trust and attitude has been further demonstrated in Molesworth and Koo (2016), which developed and tested a 20-item remotely piloted passenger aircraft attitude scale. The

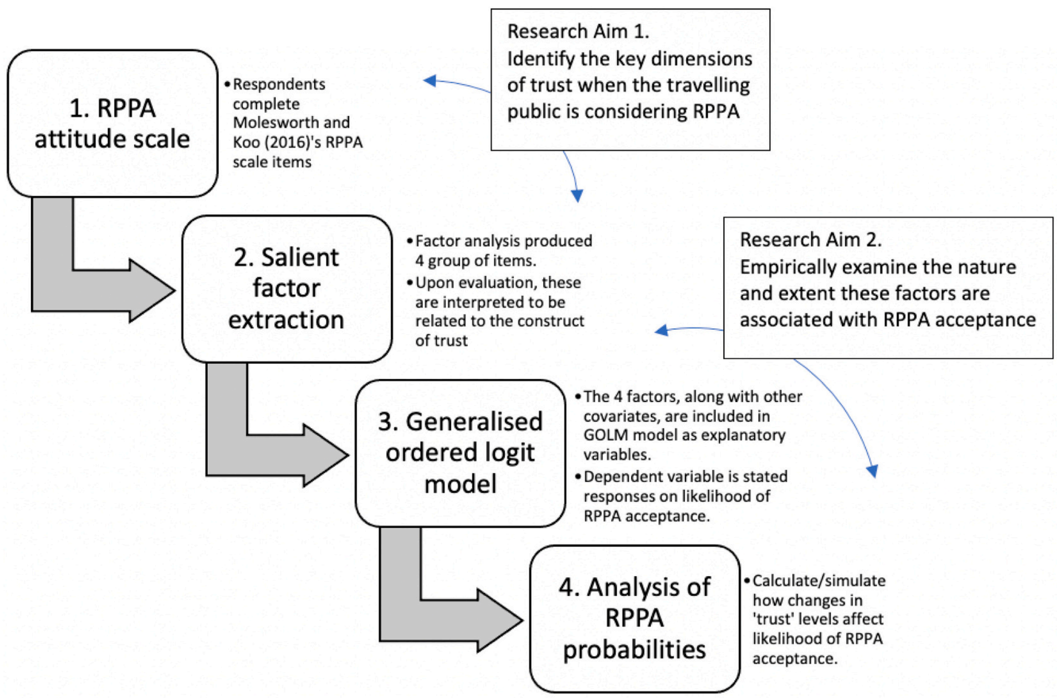

Fig. 1. Schematic diagram of the research.

items were initially generated with a focus group of experienced aviation professionals. The factoring process, including the test-retest reliability, produced two components, which the study has considered them to be best termed 'trust in on-board pilot' and 'trust in remotely piloted aircraft' (the latter is a combination of trust in the remote technology as well as the trust in the remotely located pilot). In the subsequent stage of their analysis, the individual's scores on these two components had significant influence on the stated choice of remotely piloted aircraft vs. conventionally piloted aircraft.

In fact, the importance of trust in public acceptance is already well known. Based on a review of ground autonomous vehicles research, Adnan, Md Nordin, Bahruddin, and Ali (2018) concludes that a high level of trust is the barrier that needs to be surpassed in order for users to accept them. Straubinger et al. (2020) observes factors determining automated ground vehicle acceptance such as perceived reliability of automation and perceived vehicle's safety are directly applicable to UAM. Indeed, while trust traditionally relates to the technology functioning as expected (Muir, 1987), with remotely piloted aircraft, including UAM, and as also observed in ground AV context (Xu et al., 2018), trust extends beyond the traditional view of 'fit for purpose' or 'reliability', to include *safety*, due to the potential loss of life. For example, Keller, Adjekum, Alabi, and Kozak (2018),in the study of public utility potential of pilotless aircraftfound that trust significantly correlated (0.53) with safety-risk benefits whereas the correlation with other factors were negligible.

The observations by Slovic (1987) on trust and acceptance of new technology are applicable here; that is, trust can explain the gap between experts' safety assurances (or objective safety risk) and the public's lack of acceptance. Trust is a heuristic used to make complicated decisions in the absence of knowledge to assess the benefits and risks and may be more applicable in a setting where there is not a strong positive sentiment (e.g., conservation of charismatic megafauna has strong positive sentiments) and where the entity to whom trust is to be held (e.g., technology firms, regulators, etc.) is fairly well defined (Siegrist, 2019). In fact, trust in an institution or person may differ from trust in an object because, for example, an object may lack the motive to deceive; therefore, it is possible for a user to accept a technology but not trust the industry or the institution (Siegrist, 2019). Hence, in the study of the effect of trust on acceptance, we can anticipate the analysis to involve at least two dimensions of trust (e.g., trust in the technology, trust in the institution), and these dimensions of trust may relate differentially to acceptance. Against this background, the ensuing section explains the methodology used to extract and test hypotheses about these dimensions of trust.

3. Method

3.1. Remotely piloted passenger aircraft scale (RPPAS) & exploratory factor analysis

This study applies the scale introduced in Molesworth and Koo (2016) (Table 1), which was developed with an expert focus group and

Table 1
20-item RPPA attitude scale (Molesworth & Koo, 2016).

Item #	Item Description
1	Data link systems are reliable
2	With technology nowadays, all problems can be resolved remotely
3	Pilot fatigue is better managed with remotely piloted aircraft
4	I would fly on a remotely piloted aircraft
5	All make of aircraft are as safe as each other
6	Pilots are dependable
7	Remotely piloted aircraft are as safe as traditional aircraft with pilots
8	It is the airline itself that determines safety not the make of aircraft
9	Flying is safer than driving
10	With technology nowadays, there is no need to have a pilot on-board
11	If remotely pilot aircraft weren't safe, the regulator/s would not permit them to operate
12	Having a pilot on-board an aircraft is better if a problem arises
13	All airlines are as safe as each other
14	I can trust the aviation regulators
15	It is the make of aircraft that determines safety not the airline
16	I am confident aviation safety regulators will keep the industry safe
17	Pilots on-board aircraft are reliable
18	I trust the pilot on the ground to solve any problems that may arise while controlling the remotely piloted aircraft
19	I trust the pilot in the aircraft to solve any problems that may arise
20	I trust the data link system that will transmit flight control inputs

tested with undergraduate student samples in science and engineering.

An Exploratory factor analysis using principal axis factoring was employed. Various rotation methods were attempted with Kaiser normalisation, including orthogonal varimax and quartimax, as well as oblique techniques such as promax to improve interpretability. The analysis eventually settled on the latter. As recommended by Hayton, Allen, and Scarpello (2004), a meaningful extraction of factors was based on a combined consideration of domain knowledge, the eigenvalues, scree plot, % variance explained and parallel analysis. The acceptance scale result was then used as the dependent variable to address the second research question using Generalised Ordered Logit Model (GOLM).

3.2. Generalised ordered logit model (GOLM)

The identified factors in 3.1 were converted into a score for each individual using the formula for oblique factors (see Di Stefano, Zhu, & Mîndrilã, 2009). The factor scores are standardised with mean zero and variance equal to the squared multiple correlation. Thus, the regression method locates each sample's factor scores along a distribution and the score is quantified as the number of standard deviations from the mean factor score. These factor scores were then inputted into an ordered logit model to classify respondents on the likelihood of pilotless aircraft usage. A proportional-odds model and generalised logit model (GOLM) were estimated to test for generic coefficients. GOLM takes the following form with a logit link function, $g(X_i\beta_j)$ (for further details on GOLM and codes, refer to Williams (2006)):

$$P(Y_i > j) = \frac{exp(\alpha_j + \boldsymbol{X}_i\beta_j)}{1 + exp(\alpha_j + \boldsymbol{X}_i\beta_j)} \tag{1}$$

Where $j = 1,2, \ldots, M\text{-}1$ where M is the number of categories in the dependent variable. In this study, $M = 5$. The estimation problem is to find the threshold values (α, β) that 'cuts' the cumulative probability distribution function. Thus, the model provides information on the probability (or in odds) of the likelihood of a respondent answering the 'j or less' versus 'more than j' category. In the case of the proportional-odds model (or the ordered logit model), the subscript j on the parameter β_j is dropped, assuming a generic coefficient across all categories. As will be seen, excluding the constant, a mix of three generic (one factor, gender and risk perception) and four category-specific (three factors and age) coefficients are specified in the final model. All analysis was undertaken with STATA.

3.3. Dependent variable and the covariates

Asking about expectations of behaviour (e.g., "how likely are you to do X?") rather than intent (e.g., "do you intend to do X?") carries more predictive validity because the former triggers the respondents to think about the factors that may be barriers to achieving their intent (Sheeran, 2002: p.12). Taking this into account, the dependent variable is a response on the following question "In this exercise, you will be asked to rate the likelihood that you will accept the use of a remotely piloted vehicle as a passenger. As a potential passenger in a remotely operated vehicle, how likely are you to travel in such a vehicle?" The responses were obtained on the five point scale (i.e., ordinal), based on acceptance: "very unlikely", "unlikely", "neutral, "likely", "very likely". Participants' perception of the risk involved in pilotless and driverless vehicles was also included. Risk perception was obtained from the respondents using the questionnaire in Fig. 2. In addition to the scoring on the 20 scale items, demographic information on age, income and gender, as well as their risk perception on pilotless and driverless vehicles were collected.

3.4. Participants

The survey was administered via a survey company online in Q1 2018 with gender and age-based population stratification representative of the Australian population. The survey took on average 15 min to complete. After removing incomplete responses, 501 of 557 samples remained.

Please indicate your likelihood of acceptance on a scale of 1-5, as well as the risk that you associate with each on a scale of 1 to 100.

Acceptance scale guide (1-5)
1 = Very unlikely to accept
2 = unlikely to accept
3 = neutral
4 = likely to accept
5 = very likely to accept

Risk scale guide (1-100)
1 = virtually zero risk involved in this situation. It is about as safe as sitting on the couch watching TV.
50 = The same amount of risk as driving your car on a freeway in moderate traffic and good weather conditions during the day.
100 = Extremely high risk of a serious, probably fatal injury. The passenger will be very fortunate to escape from this situation alive and with the vehicle undamaged.

Q1. In this exercise, you will be asked to rate the likelihood that you will accept the use of a remotely piloted/operated/driven vehicle as a passenger.

Remotely operated vehicle	As a potential passenger in a remotely operated vehicle, how likely are you to travel in such a vehicle? (please choose 1, 2, 3, 4, or 5)	As the passenger in a remotely operated vehicle, state the perceived level of risk
Aircraft	Point and Click buttons (very unlikely) 1 2 3 4 5 (very likely)	INSERT BOX (1-100)
Car	Point and Click buttons 1 2 3 4 5	INSERT BOX (1-100)
Public bus	Point and Click buttons 1 2 3 4 5	INSERT BOX (1-100)
Train	Point and Click buttons 1 2 3 4 5	INSERT BOX (1-100)

Fig. 2. Excerpt of the survey.

4. Results

4.1. Descriptive statistics

Table 2 shows the age, gender and geographic distribution of the samples, which conform to the Australian Census 2016.

Table 3 displays the perceived risk distributed across the four transportation modes. As can be seen in this table, perceived risk (out of 100) was highest for remotely piloted aircraft, which was confirmed to be significantly different from remotely operated car, bus and train at 1% level. As shown in Table 4, the majority (58%) of the respondents indicated they are "unlikely" or "very unlikely" to accept the remotely piloted aircraft as a passenger, whereas 23% indicated "neutral" and the remaining 19% "likely" or "very likely".

4.2. Factor analysis

Average scores on the 5-point scales ranged from 3.45 (SD 0.95) and 2.20 (SD 0.78). Parallel analysis revealed that up to 7 factors can generate explanatory power of the variation in the data, however, this drops off quickly from around the 3rd or 4th factor. Although Eigenvalue >1 factor retention rule (aka. Kaiser >1 criterion (K1)) is a commonly applied method, parallel analysis, which is the most accurate method available (Hayton et al., 2004), is suggestive of 4 factors.

Once the decision to retain 4 factors was made, an extensive exploratory factor analysis was undertaken, using Promax rotation (an oblique rotation method). Although the solution was similar to an orthogonal varimax method, the Promax provided improved interpretability through a more pronounced partition. The four factors accounted for 60% of the variation. 14 of the 20 items had a uniqueness below 0.6 or communalities exceeding 0.4. Three items exceeded a uniqueness of 0.7 while a further three items exceeded 0.6 although these were all low 60s (<0.62). Variation to the methods, such as quartimax and Kaiser/Horst normalisation were applied. These did not deviate from the finalised results in a way that negated the solution. As shown in Table 6, factors were labelled "Trust in remotely piloted aircraft (RPA)", "Trust in Aircraft manufacturer/make", "Trust in on-board pilot and aviation regulators", and "Trust in airline/services provider". It can be seen in Table 6 that three items (#5, #6, #11) loaded onto more than one factor with the loading of at least 0.3.

As a robustness check, it is noted that when the same methodology (*principal components* analysis with orthogonal varimax) used in Molesworth and Koo (2016) is applied to the current 501 sample, the above 4 factor solution is supported. The current study was able to show the efficacy of the scales initially developed using a narrow population of

Table 2
Sample characteristics.

	Sample	Australian Census 2016
Gender (female)	51%	51%
Age group		
18–24	12%	11%
25–34	19%	20%
35–44	17%	18%
45–54	17%	17%
55–64	17%	15%
over 65	19%	21%
Geography		
Aus. Capital Territory	2%	2%
New South Wales	31%	32%
Victoria	27%	23%
Queensland	20%	20%
South Australia	7%	7%
Western Australia	10%	12%
Tasmania	2%	3%
Northern Territory	1%	1%

Table 3
Perceived risk across four modes.

	Mean	Standard Deviation
Remotely operated aircraft	66	27
Remotely operated car	62	25
Remotely operated train	54	27
Remotely operated bus	60	25

Table 4
Likelihood of RPPA acceptance.

	Count	Proportion	Cumulative
Very unlikely to accept (1)	199	40.04	40.04
Unlikely to accept (2)	90	18.11	58.15
Neutral (3)	113	22.74	80.89
Likely to accept (4)	55	11.07	91.95
Very likely to accept (5)	40	8.05	100

Table 5
Parallel analysis.

Number of factors	Factor Analysis (eigenvalues)	Parallel Analysis	Difference
1	5.2686	0.4105	4.8580
2	2.5735	0.3426	2.2309
3	0.7887	0.2950	0.4936
4	0.4874	0.2474	0.2399
5	0.2950	0.2086	0.0864
6	0.2221	0.1720	0.0500
7	0.1677	0.1365	0.0312
8	0.0930	0.1027	−0.0096
9	0.0396	0.0706	−0.0309
10	−0.0276	0.0378	−0.0654

Note: As can be seen in Table 5, although it may be still considered an improvement, the difference from the 5th factor decreases to negligible level - 0.086 – and almost indistinguishable from random results.

Table 6
Promax rotation (score > 0.3 only reported).

Items	Trust in remotely piloted aircraft (RPA)	Trust Aircraft Manufacturer/ Make	Trust in On-board pilot/ aviation regulators	Trust in airline/ services provider	Uniqueness
1	0.5688				0.6047
2	0.5001				0.5706
3	0.6738				0.6194
4	0.8622				0.3784
5		0.5799		0.3127	0.4446
6			0.579	0.3079	0.6121
7	0.7568				0.3296
8				0.3678	0.7807
9				0.3827	0.7788
10	0.722				0.4248
11	0.4413		0.3999		0.6194
12			0.531		0.5732
13		0.6581			0.5855
14			0.6072		0.4559
15		0.4542			0.7738
16			0.6256		0.3988
17			0.7997		0.3958
18	0.5502				0.5035
19			0.6744		0.5712
20	0.5809				0.4606

Note: score < 0.3 is left blank for convenience and it does not suggest the blank cells are replaced with '0' loadings.

study (students). The wider sample, as expected, provided more information about the general public's attitudes and perceptions about remotely piloted passenger aircraft (RPPA). Subsequently, section 3.1these loadings were then used as weights to generate factor scores. The next step was to determine which trust factors are associated with acceptance. When the scores are used as inputs, the GOLM essentially tests these hypotheses.

4.3. Generalised ordered logit model (GOLM)

First, responses on acceptance likelihood were used as a dependent variable in an ordered logit model. The proportional odds assumption was tested and subsequently the trust in aircraft make, age and risk perception variables were constrained to be fixed across the categories, whereas the remaining parameters were allowed to vary as they had a statistically differential impact for each category. Income was not found to be significant in any categories at the 5% level and therefore, was dropped from the final model. The log likelihood at convergence was −592.883 which yielded a pseudo R^2 of 0.182. Coefficients are displayed in odds-ratio (OR). As shown in Table 7, all but 3 variables (gender, risk perception, and trust in aircraft make) violate the proportional odds assumption, suggesting considerable non-linearity and asymmetry in the relations between these variables and RPPA acceptance.

4.3.1. Coefficients on extracted factors

One standard deviation (SD) increase in the trust of RPA increases the odds of moving up from "very unlikely" to "unlikely or above" by 3.95; that is, 395%. This increase occurs at a decreasing rate, as moving from neutral (and below) to "likely" or "very likely" is 2.36, and moving from likely (and below) to "very likely" is 1.83. Clearly, trust in remotely piloted aircraft ("trust in RPA" herein) is the strongest covariate. 'Trust in aircraft manufacturer' was specified as a generic parameter across the categories. It has a coefficient of 0.86, but not statistically significant based on conventional threshold (p-value <0.05). Similarly, 'Trust in airline/service provider' has negative coefficients but they are not statistically significant with p-values exceeding 0.05.

An increase in one standard deviation with 'trust in pilot on-board and regulators' is associated with 0.73 change in odds ratio with respect to the category "very unlikely". That is, the odds of moving beyond "very unlikely" decreases (by 27%) as 'trust in pilot on-board and regulator' increases by 1 SD. While the coefficient is similar for the "unlikely" category, it has no statistically significant effect in tipping a person on a neutral position towards greater likelihood of acceptance. Importantly, this relationship appears to flip signs – the positive coefficient (i.e., >1) in category 4 (or "likely") suggests greater 'trust in pilot on-board and regulators' is associated with greater likelihood of moving from "likely" (or below categories) to "very likely" by 52% (OR of 1.52). This U-shaped effect is captured through GOLM and is illustrated in Fig. 3 and Fig. 4 where the coefficients are converted into probabilities using the delta-method. Y-axis shows the marginal effect of one unit (SD) change in trust in RPA on the probability of a category (e.g., "very unlikely"), i.e., one unit increase in trust in RPA reduces the probability of "very unlikely to accept" by 0.23, but increases the probability of "neutral" by 0.14, and "likely to accept" by 0.07. Focusing on the two main trust factors of influence, we note the contrasting patterns where trust in RPA shows an inverse U-shaped effect whereas trust in pilot and regulators shows a U-shaped effect. That is, higher scores on trust in RPA increases the probability of acceptance but only up to a point ("neutral") and from therein the effect decreases. The converse of this is true for trust in pilot and regulators where one unit increase in trust has a decreasing effect on the probability of "neutral" but positive marignal effect on the probability of "very unlikely" and "very likely".

4.3.2. Coefficients on risk perception, gender and age

The effect of gender varies across categories. The most prominent

Table 7
GOLM results.

Likelihood of acceptance	Odds Ratio	Std. Err.	P-vaue	[95% Conf.	Interval]
Very Unlikely (category = 1)					
Trust in remotely piloted aircraft (RPA)	3.9505	0.7497	0.0000	2.7234	5.7304
Trust in aircraft manufacturer/make	0.8627	0.1443	0.3770	0.6216	1.1975
Trust in on-board pilot/ regulators	0.7303	0.0945	0.0150	0.5666	0.9412
Trust in airline/service provider	0.9440	0.1454	0.7080	0.6980	1.2766
Female	0.5325	0.1213	0.0060	0.3408	0.8321
Age	0.9823	0.0057	0.0020	0.9712	0.9934
Risk perception	0.9847	0.0036	0.0000	0.9777	0.9917
Constant	15.1080	6.3064	0.0000	6.6665	34.2386
Unlikely (category = 2)					
Trust in remotely piloted aircraft (RPA)	5.0113	0.9647	0.0000	3.4363	7.3081
Trust in aircraft manufacturer/make	0.8627	0.1443	0.3770	0.6216	1.1975
Trust in on-board pilot/ regulators	0.7030	0.0951	0.0090	0.5393	0.9165
Trust in airline/service provider	0.7478	0.1151	0.0590	0.5531	1.0110
Female	0.6472	0.1400	0.0440	0.4235	0.9890
Age	0.9823	0.0057	0.0020	0.9712	0.9934
Risk perception	0.9847	0.0036	0.0000	0.9777	0.9917
Constant	4.3172	1.7430	0.0000	1.9568	9.5251
Neutral (category = 3)					
Trust in remotely piloted aircraft (RPA)	2.3597	0.4523	0.0000	1.6207	3.4357
Trust in aircraft manufacturer/make	0.8627	0.1443	0.3770	0.6216	1.1975
Trust in on-board pilot/ regulators	1.2501	0.2074	0.1790	0.9030	1.7305
Trust in airline/service provider	1.0544	0.2007	0.7810	0.7261	1.5311
Female	0.9548	0.2355	0.8510	0.5888	1.5482
Age	0.9823	0.0057	0.0020	0.9712	0.9934
Risk perception	0.9847	0.0036	0.0000	0.9777	0.9917
Constant	1.1098	0.4547	0.7990	0.4971	2.4776
Likely (category = 4)					
Trust in remotely piloted aircraft (RPA)	1.8282	0.4604	0.0170	1.1160	2.9948
Trust in aircraft manufacturer/make	0.8627	0.1443	0.3770	0.6216	1.1975
Trust in on-board pilot/ regulators	1.5249	0.3463	0.0630	0.9771	2.3798
Trust in airline/service provider	0.8222	0.2107	0.4450	0.4976	1.3585
Female	0.8841	0.3216	0.7350	0.4333	1.8037
Age	0.9823	0.0057	0.0020	0.9712	0.9934
Risk perception	0.9847	0.0036	0.0000	0.9777	0.9917
Constant	0.4034	0.1882	0.0520	0.1616	1.0067

Note: Wald test results are as follows – where significant test results at 5% level show violation of the parallel lines assumption: trust in RPA (p-value - 0.00); trust in pilot/regulators (0.00); trust in airline (0.00); trust in aircraft make (0.89); age (0.03); gender (0.39); and risk perception (0.33). As a side, due to the similarity of item #4 in the attitude scale with the dependent variable, the same analysis described in section 3.1 was repeated with #4 excluded. With the exception of the diminished significance of the fourth factor – trust in airline services providers, which is of minor significance, the patterns in the estimated coefficients (such as the relative sizes of the coefficients, statistical significance and +/− signs) did not change in a way that negates the ensuing results.

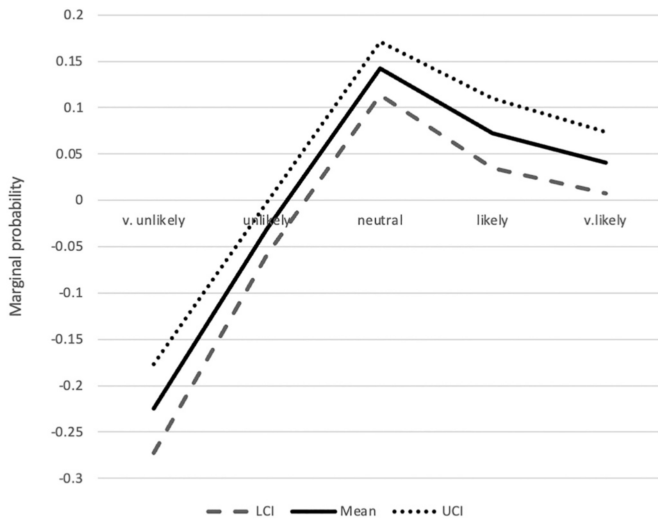

Fig. 3. Trust in RPA on probability of acceptance (with lower confidence interval (LCI) and upper confidence interval (UCI))

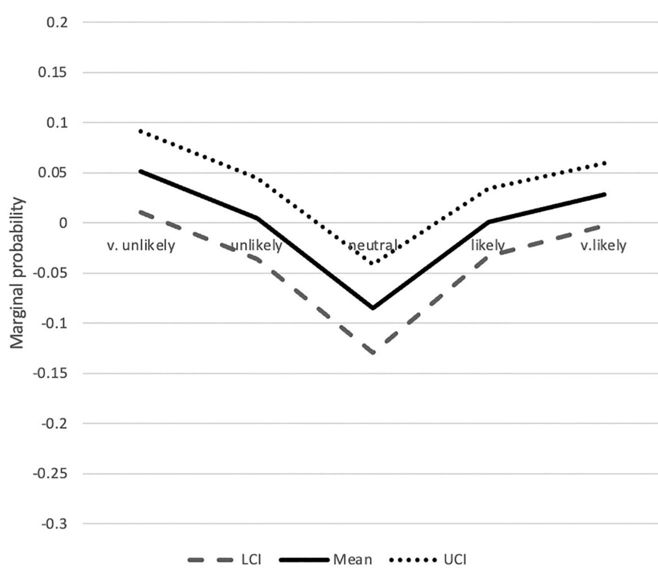

Fig. 4. Trust in pilot and regulators on probability of acceptance.(with lower confidence interval (LCI) and upper confidence interval (UCI))

association of gender can be seen in the "very unlikely" category where female is associated with approx. 50% (OR of 0.53) less likelihood of moving beyond this response. This conforms to the existing evidence about the greater propensity of males to take on the new travel mode (e.g., BAH, 2018). However, this association is not prevalent across all categories. While the OR of 0.65 is statistically significant at the 5% level for the "unlikely" category, the estimated effect disappears in subsequent responses with "neutral" and "likely" having an OR of 0.95 and 0.88, respectively, and both with very large standard errors. That is, among those "unlikely to accept", there appears to be a gender differential. However, such gender differential does not exist among the population who gave "neutral" or "likely to accept" responses. This is an L-shaped effect, which can be illustrated when the OR is converted into probabilities (Fig. 5). On average, female respondents are 10 percentage points more likely to report they are "very unlikely" to accept RPPA than male respondents (Fig. 5). This difference in gender disappears as one moves closer to acceptance, showing the L-shaped influence.

Consistent with earlier findings (e.g., BAH, 2018), age does have a significant effect throughout all responses. Specifically, with the OR of

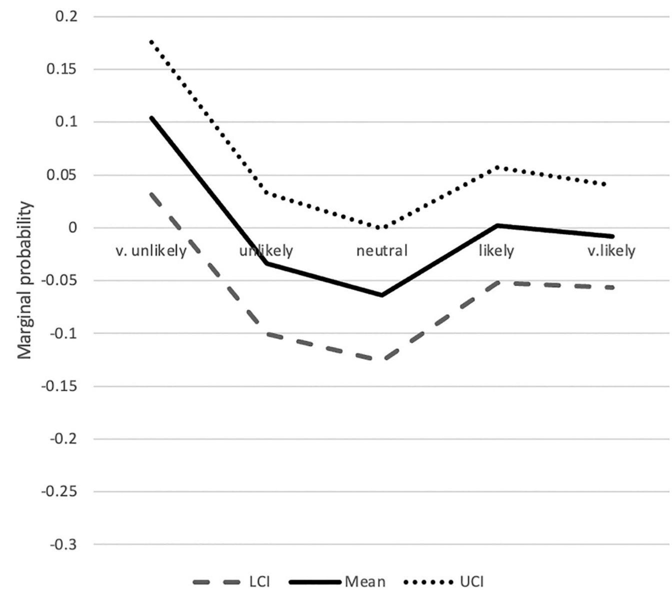

Fig. 5. Gender and probability of acceptance.(with lower confidence interval (LCI) and upper confidence interval (UCI))

0.98, a one year increase in age is associated with a 2% decrease in odds of moving towards acceptance. This effect is consistent across all categories (note the generic parameter). The mean age of "very unlikely to accept" response is 51 years old whereas the mean age for "very likely to accept" is 39 years old. Overall, there is a steady decline from 51 to 39 years as one moves from "very unlikely" to "very likely acceptance". Similar to age, risk perception with respect to RPPA has a generic parameter. The OR of 0.98 indicates one unit increase in perceived risk is associated with a 2% decrease in the odds of acceptance.

4.4. Probabilities of acceptance

The parameterised GOLM can be used to simulate how changes in the trust levels change acceptance likelihoods, assuming all other covariates remain constant. In Figs. 6 & 7, note the five probabilities sum to one vertically. The vertical bars for each category are 95% confidence intervals. The horizontal axis shows the standardised factor scores (refer to section 3.4 for details); therefore, it ranges approx. ∓3 and a respondent with an average factor score would be located at '0'. In Fig. 6, for that 'average' person, the response with the highest probability is 'very

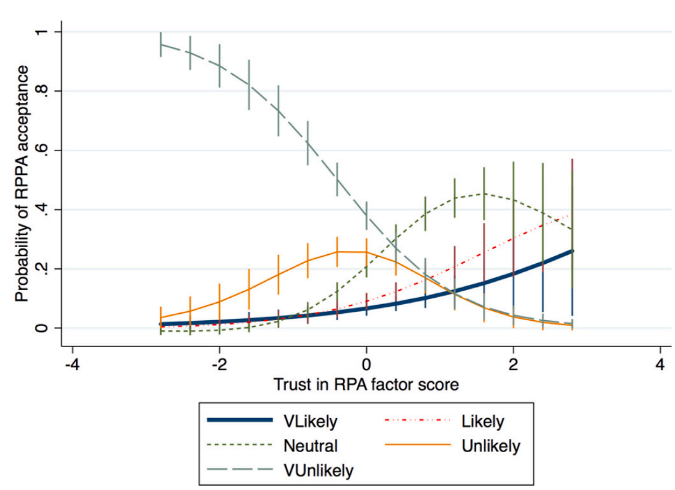

Fig. 6. Trust in RPA and probability of acceptance. Note: vertical bars are 95% CI.

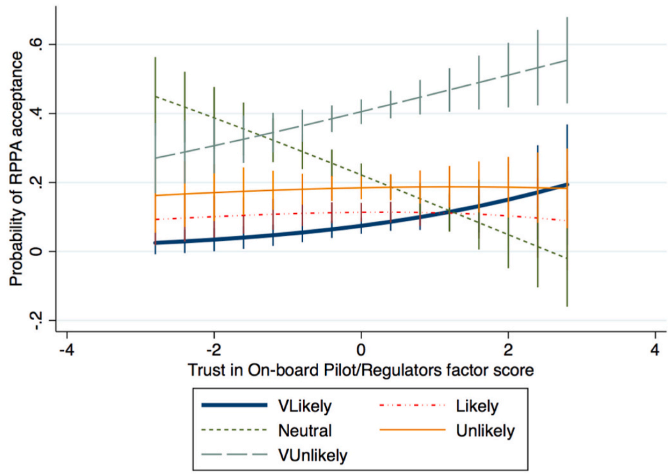

Fig. 7. Trust in On-board Pilot or Aviation Regulators and probability of acceptance. Note: vertical bars are 95% CI.

unlikely to accept' (~0.4 probability on the vertical axis), while the response with the lowest probability is 'likely' or 'very likely' (~0.05) – the two categories overlap significantly in the confidence intervals.

Fig. 6 shows the effect of trust in RPA on likelihood of acceptance is positive but at a diminishing rate. For those with a very low level of trust (i.e., 2 SD below the mean), the probability of a "very unlikely" response (i.e., not accepting) is very high (0.9). Probability declines rapidly, reaching 0.4 at the mean trust level. That is, for those with an average level of trust, the probability of responding "very unlikely" is 0.4 and "unlikely", 0.25. However, for higher level of trust (i.e., as the individual's trust scores increase beyond the mean), the effect on acceptance is diluted and less certain; for instance, at 2 SD above the mean, 'neutral' and 'likely' have similar probabilities (~0.3–0.4), 'very likely' (~0.2) and the remaining probabilities are spread among 'very unlikely' and 'unlikely'. That is, a very high degree of trust in RPA cannot predict the likelihood of acceptance to the same level of certainty as a very low degree of trust in RPA can predict the likelihood of non-acceptance.

One of the interesting results is the co-location of the items involving trust in pilot on-board and trust in the regulator. Experts and laypersons may differ in how trust plays a role in the decision making; for instance, experts may evaluate the ability factors of the government whereas laypeople may rely on their own trust in the institution (Siegrist, 2019). Unlike driving, passengers often do not have access to the pilot's tasks, and in the absence of knowledge on the ability attributes of the pilot and how pilots are involved across different semi-autonomous/autonomous configurations, laypersons may instead rely on their trust in the institutional or governmental entity/regulator overseeing the safety of air services. The data show those with lower (greater) trust or confidence in the pilot on-board tend to have lower (greater) trust in the regulator.

With respect to the factor's relation with acceptance, an interesting finding is a pattern of polarisation. Fig. 7 shows the polarising effect of this factor on probability of acceptance. This can be observed by the decrease in the probability of 'neutral' from 0.4 to 0.0 as the factor score increases. This significant decline in the 'neutral' position is taken up by (1) 'very unlikely to accept', which increases in probability from 0.25 to ~0.6 and (2) 'very likely', which increases in probability from ~0.0 to 0.2. The moderate categories – 'likely' or 'unlikely' – remain more or less constant. Upon closer inspection, this polarisation is traced to the trust in RPA. Respondents with *low* trust in RPA and *high* level of trust in onboard pilot and regulator are likely to choose "very *unlikely* to accept", whereas respondents with *high* level of trust in RPA and *high* level of trust in onboard pilot and regulator are likely to choose "very *likely* to accept". This means, even if the user has a high level of trust in the pilot on-board and the regulating body, the outcome with respect to RPPA acceptance can be drastically different depending on their existing views on the reliability and safety of RPA technology.

5. Discussion

Urban Air Mobility has significant potential to improve productivity through alleviating congestion in cities. However, user acceptance of this technology is not guaranteed and the trust in this technology is one of the impediments to its success. Therefore, the main aim of the present research was to identify attitudinal factors related to trust when the travelling public is considering remotely piloted aircraft. In pursuit of this aim, the first research question sought to identify the salient attitudinal factors relating to trust with RPA. Using a tested scale, the results revealed four factors of attitudinal trust relating to RPA. The four factors identified are: (1) trust in remotely piloted aircraft technology; (2) trust in pilot onboard and the regulating body; (3) trust in aircraft manufacturer/make; and (4) trust in airline service provider.

The second research question sought to understand how these factors relate to willingness-to-accept RPA. The results revealed the first two factors are key (i.e., strong empirical support) when it comes to willingness-to-accept. These two factors relate specifically to the technology of the RPA, the pilot onboard the aircraft and the governing body that oversees the technology. The other two factors relate to the commercial entities involved in the delivery of the service (i.e., aircraft manufacturer and airline). The findings specific to the first factor revealed that 'trust in technology' increases acceptance, but at a diminishing rate. In other words, a very high degree of trust cannot predict the likelihood of acceptance to the same level of certainty as a very low degree of trust can predict the likelihood of non-acceptance.

In terms of the second factor, the results revealed that 'trust in pilot onboard and regulator' produces polarisation in acceptance. This polarised view is consistent with the findings from public acceptance studies on automated vehicles (Garrow et al., 2022). However, earlier studies have not identified to which trust dimension the polarisation may be related.

5.1. Theoretical implications

These findings highlight the complexity of the associated factors involved in developing/improving individuals' trust in RPA. From a theoretical perspective, the study reveals the following. First, it illustrates the existence of several trust factors, confirming the generalisability of earlier observations in the transport automation context (Hengstler, Enkel and Duelli, 2016). Second, it shows the differing importance each trust factor has with respect to willingness-to-accept the new technology, especially in the very early stages of market development. The importance of this cannot be underestimated, especially in the context of the present research, as UAM and pilotless aircraft are presently trying to obtain a foothold in a widely trusted and mature market (i.e., commercial aviation) and knowing their relationship with willingness-to-accept can help guide and target intervention.

Third, and possibly most important, the findings highlight the need to explicate the four trust factors in theoretical technology acceptance models/frameworks, paying particular attention to the non-linear, polarising and asymmetric relationship with willingness-to-accept. Inclusions in such models have the potential to highlight the multidimensional role of trust in user acceptance of this new mode of air travel (i.e., UAM, remotely piloted and pilotless aircraft), and explore how this may change as a result of factors such as exposure, individual age, maturity of technology and product development to name a few. Such an inclusion is important in generating new hypotheses, thereby facilitating in the societies' understanding about the complex and important factor of trust. By extension, relationships between other factors of cognizant and emerging technologies such as drone ownership, drone interests with RPPA acceptance may also be explored.

5.2. Managerial implications

From an applied perspective, these findings provide clear guidance as to the important factors that need to be considered and targeted if operators are to attract users to this new technology. While the factors that influence user acceptance are clear, as regulatory/legislative changes evolve/mature, and unfortunately the inevitable will occur, specifically incidents and accidents, all parties with a vested interest in the success of UAM will need to have a plan to minimise the loss of trust in this technology. The results suggest resources should focus on minimising extreme distrust in the RPA technology. This effort will build trust in areas where greatest increases in adoption probability (in the margin) may occur but also reduce polarisation. While not to be entirely neglected, results indicate that airline and aircraft manufacturer factors are not forefront at the early stages of building trust.

The results have implications for technology management. Understanding and modelling polarisation effect (and how to reduce it) is particularly important because it is often the behaviour of those at the extreme end that may be pivotal. For instance, the attitude and behaviour of those in the very accepting end are early adopters who will propagate the technology as well as help start the industry as they prepare for scaling. Those in the other end may have strong concerns and may be disproportionately (more or less) represented through channels such as the media and public forum. As the polarised views imply, the perceived deficiency in one attribute (such as no pilot on-board) may not be readily compensated for by improvement in other attributes (such as reduced price). Thus, and as acknowledged in the ground AV literature as well (Hancock et al., 2019), a sustained period where mixed aircraft configurations co-exist is highly probable. Therefore, in addition to the messaging and engagement activities that focuses on minimising extreme level of distrust in the RPA technology, providing consumers the option to voluntarily choose from a multiple range of aircraft configurations in the market offers a robust approach in light of these polarisations and non-linear patterns of trust. These configurations may involve variations such as “piloted”, “remotely piloted with a flight attendant on-board”, “remotely piloted without a flight attendant on-board”, “automated, with a flight attendant on-board”, and “automated, without a flight attendant on-board”. However, more research is needed because, a priori, the suitable product mix is not always obvious; for example, Ward et al. (2021) did not find evidence that potential users discriminate between remotely piloted and pilotless air vehicles.

5.3. Limitations and future research

As with many studies investigating a construct such as attitude towards a new, and in some cases hypothetical object or situation, reliability and validity is of concern (Sheeran, 2002). Hence, the results of the present study need to be viewed with this in mind. How the results may differ, if at all based on different nationalities or exposure to different levels of technology also remains unknown. As UAM develops, it is feasible that other factors may arise that have not fully been considered or explored. For example, noise pollution (i.e., cognitive effect; Molesworth & Koo, 2016) from such technology may be front and centre when it comes to user acceptance. It is also plausible that privacy concerns may arise as well as from an environmental perspective, the life cycle of the crafts, including the materials and resources used to produce them may impact on user acceptance. As noted by Garrow, German and Leonard (2022), due to different adoption rates, changes in populations, the introduction of competing technologies, etc., it will be important to conduct UAM adoption studies across time to ensure robust results. Hence, all areas for future research.

6. Conclusion

A critical aspect of public acceptability of a new transport technology such as UAM is attitude and its roles in influencing willingness-to-accept. Scaling the operation is necessary to drive down unit costs, yet scaling potential is limited by the inelastic pilot market characteristics. In this context, one of the key issues concerns the trust the travelling public places on air travel that reduces, or even removes, the pilot’s role. Against this background, the paper aimed to (1) identify the key factors related to trust when the travelling public is considering remotely piloted passenger aircraft (RPPA) and (2) empirically examine the nature (coefficient signs) and extent (coefficient magnitude) these factors are associated with the willingness-to-accept an RPPA, conditional on key variables such as age, gender and perceived risk.

In achieving the first aim, the scale had some success in extracting meaningful factors, by being able to isolate into categories with stakeholder implications. The factor solutions produced were “Trust in RPA”, “Trust in Aircraft manufacturer/make”, “Trust in on-board pilot and aviation regulators”, and “Trust in airline/services provider”. In addressing the second aim, the analysis strategy employed revealed new insights. First, the effects of trust were asymmetrical where increase in trust above and beyond the average has limited effect on acceptance, while loss of trust below the average level- significantly reduces acceptance. Second, trust in pilot on-board and regulators have a polarising effect. Increase in this trust increases the probability of acceptance or rejection at the expense of the neutral position. Even if the user has a high level of trust in the pilot on-board and the regulating body, their RPPA acceptance likelihood could be high if their views on the reliability and safety of RPA technology are favourable. While polarisation in acceptance is consistent with earlier findings in cognizant context, this study was unique in that it was able to shed data-driven insights on the dimensions of trust closely linked to such polarisation, enriching our understanding of how pilotless aircraft industry could conceivably serve our society.

CRediT authorship contribution statement

Tay T.R. Koo: Conceptualization, Methodology, Validation, Formal analysis, Supervision, Project administration, Writing - original draft, Writing - review & editing. **Brett R.C. Molesworth:** Conceptualization, Investigation, Writing – original draft, Writing – review & editing, Resources. **Matthew J.M. Dunn:** Conceptualization, Formal analysis, Writing – review & editing, Visualization. **Gabriel Lodewijks:** Funding acquisition, Writing – review & editing, Supervision. **Shirley Liao:** Conceptualization, Methodology, Formal analysis.

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