Journal of Aviation/Aerospace Education & Research

Volume 29
Number 1 *JAAER 2020*

Article 3

2020

Public Acceptance of AI Technology in Self-Flying Aircraft

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Scholarly Commons Citation

Talley, S. M. (2020). Public Acceptance of AI Technology in Self-Flying Aircraft. *Journal of Aviation/Aerospace Education & Research, 29*(1). DOI: https://doi.org/10.15394/jaaer.2020.1822

Introduction

Each day the Air Traffic Organization reports service to over 2.7 million airline travelers in an airspace system encompassing more than 29 million square miles (Federal Aviation Administration [FAA], 2019). In fact, statistics show that the volume of passengers and flights outweighs the number of qualified pilots available (Park, Shim, & Choi, 2015). In order to capitalize on the number of available pilots, aircraft manufacturers are outfitting their fleets with automated technologies to reduce the amount of human input required (Casner, Geven, Recker, & Schooler, 2014). Specifically, researchers have begun investigating solutions to the industry's pilot shortage through the development of self-flying aircraft (SFA) (Ellis, 2019). Additionally, the transportation industry has introduced varying types of artificial intelligence (AI), such as self-driving cars and unmanned aerial vehicles. Studies have sampled the public's general acceptance of these systems, and the results have the potential to be applied to future technologies in flight.

Public acceptance has been defined as a positive attitude towards an idea or product at the specific time of introduction (Cohen, Reichl, & Schmidthaler, 2014). Three aspects of public acceptance exist in the general framework of the model: socio-political acceptance, community acceptance, and market acceptance. The socio-political aspect is the broadest of the facets and includes acceptance of technologies and policies. Community acceptance typically includes trust and willingness to implement into culture. Finally, market acceptance is the consumer and investor facet of acceptance (Wüstenhagen, Wolsink, & Bürer, 2007). All three aspects of public acceptance are important for new technologies to be successfully introduced into society.

The following study will include a meta-analysis of existing studies on similar technologies. Since SFAs are still primarily theoretical and have only recently been investigated for testing and production, studies focusing on public acceptance of SDVs were reviewed and analyzed against the research question and hypotheses.

Research Question and Hypothesis

The research question driving the study is: What factors influence an individual's intentions to use SFA based on the public's acceptance of other AI-based technologies?

The hypotheses for the study are:

H_1: Environmental benefits positively influence an individual's intentions to use SFA.

H_2: Perceived safety risks negatively influence an individual's intentions to use SFA.

H_3: Perceived usefulness positively influences an individual's intentions to use SFA.

H_4: Perceived ease of use positively influences an individual's intentions to use SFA.

H_5: Perceived trust positively influences an individual's intentions to use SFA.

Literature Review

Research of current literature on public acceptance of autonomous vehicles, such as self-driving vehicles (SDVs) and unmanned aerial vehicles (UAVs), identifies various factors influencing an individual's intentions to use such technology. Many of these studies employ a variation of the Technology Acceptance Model (TAM), which is a widely used method of acceptance due to its reliability and validity (King & He, 2006). Essentially, the TAM measures the perceived usefulness (PU) and the perceived ease of use (PEOU) for the technology being assessed. These factors are used as predictors for a user's intent to use the technology as well as the actual usage of the technology. More specifically, PU is defined as the degree to which a person perceives the technology as being able to enhance job performance. Similarly, PEOU is defined as the degree to which a person perceives the technology as being reasonably effortless to use (Davis, 1989).

DOI: https://doi.org/10.15394/jaaer.2020.1822

The information systems theory outlined by the TAM provides a framework to measure and assess the factors that influence a user's willingness to accept a new technology. Expanded from Ajzen and Fishbein's Theory of Reasoned Action (TRA), which correlates the relationship between human attitudes and behaviors with associated actions, TAM is the most widely accepted model of technology acceptance (Venkatesh, 2000). Figure 1 depicts the TAM, as developed by Davis, Bagozzi, and Warshaw (1989).

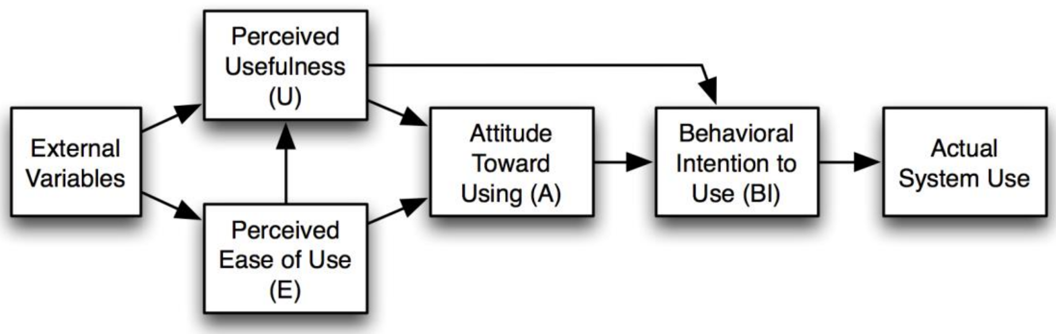

Figure 1. Technology Acceptance Model (Davis, Bagozzi, & Warshaw, 1989).

In addition to the predictor variables (PU and PEOU), the TAM also includes the user's attitude and acceptance toward using the technology being measured as well as the user's behavioral intention to use the technology being measured. The attitude factor is measured through self-reported usage of the technology by study participants. Similarly, behavioral intentions are measured through self-predicted future usage of the technology by study participants (King & He, 2006). Using a validated survey tool, the necessary information is collected and assigned a corresponding value. A Likert scale instrument is used to measure and evaluate the values collected in TAM research studies. This model has gone through extensive and rigorous reliability and validity testing and is regarded as one of the most vigorous and comprehensive models for predicting user acceptance of a technology (Legris, Ingham, & Collerette, 2003).

Self-Driving Vehicles

Since autonomous driving technology has emerged as a viable and categorical objective of the automobile industry, market analysis and research studies have been conducted to evaluate the public's perception and willingness to accept this mode of transportation (Lee & Kolodge, 2019). SDVs are being developed by a variety of companies; some of which have already implemented pilot versions within their operations, including Aptiv, Cruise, Nuro and Uber. Some, such as Aptiv and Nuro, have safety drivers behind the wheel for backup, and others, such as Cruise and Uber, are fully autonomous and are driving on public streets today. Alongside these road tests, researchers are conducting analysis on public response and attitudes towards SDVs. Many of these studies have employed the TAM, or a variation of the model, to explore public acceptance.

Liu, Zhang, and He (2019) conducted a study on SDVs and the effect of age on the perceived level of acceptable safety. The objective of the study was to determine how safe SDVs should be, according to public perception, before they should be allowed to operate autonomously on public streets. Their research consists of an expressed-preference approach to determine the level of acceptable risk based on age. Based on their hypothesis of age impacting acceptable levels of safety, the researchers first reviewed the literature to determine differences in attitude and willingness to accept change between younger and elderly populations. In response, the researchers also employed psychometric scales to identify affective, cognitive and behavioral responses to SDVs based on age. The results of their study indicated that older populations desire higher levels of safety in SDVs, and their acceptable level of safety was approximately double the level of acceptable safety of the younger participants. Participants also expressed positive attitudes towards the environmental benefits of SDVs, as well as usefulness and ease of use. However, trust in the technology was negatively impacted based on the perceived safety risks.

Liu, Yang, and Xu (2019) conducted an expressed-preference approach study using a survey to determine the socially acceptable level of risk for SDVs. Their research intent was also to determine how safe SDVs must be before they would be socially accepted on public streets. Similar to a TAM approach, the researchers built a model to measure user's acceptance of SDVs based on their perceptions and experiences with human-driven vehicles. Figure 2 depicts the model created for this study. The results indicated the public desires a higher level of safety for SDVs than standard vehicles. Participants' perceptions on risk frequency was directly related to the risk-acceptance rate. Researchers also reviewed the acceptance of SDVs based on gender. Their research suggested women are less likely to accept risk than men and have higher safety requirements, which is consistent with previous studies on gender and risk perception (Harris, Jenkins, & Glaser, 2006). Furthermore, the study showed results on perception of risk consistent with other studies, indicating negative attitudes towards SDVs.

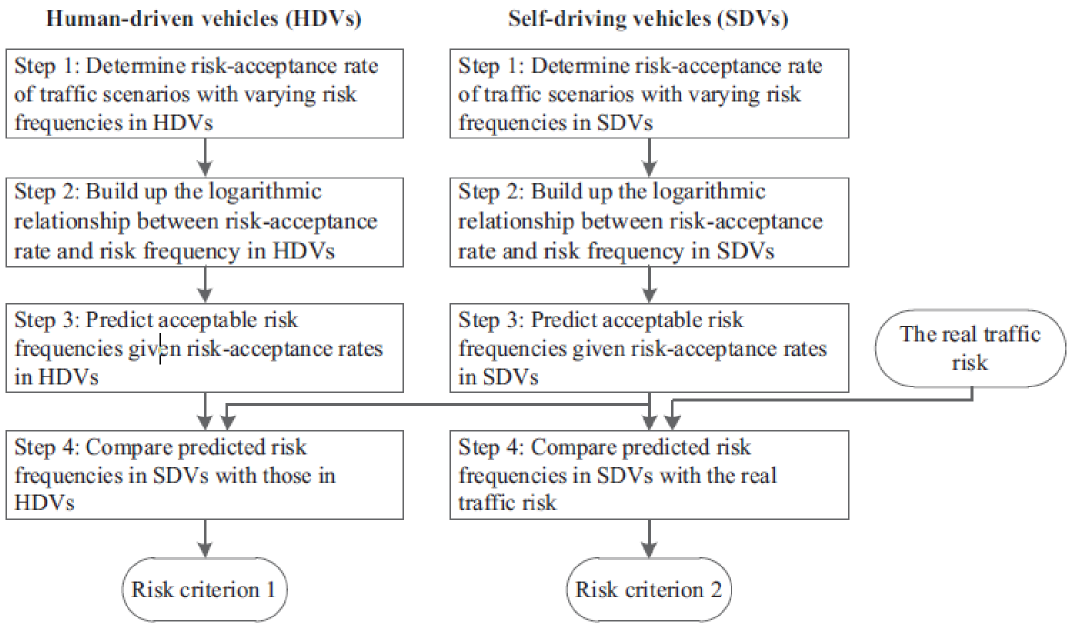

Figure 2. Expressed-preference model for measuring acceptable risk (Liu, Yang, & Xu, 2019).

Similarly, Raue et al. (2019) researched an individual's perception of SDVs based on experiences of driving regular cars. The study investigated risk perception, benefit perception and trust in addition to a general acceptance of the technology. Building on the TAM, the researchers included usability and value in their model to further expand understanding of public opinion on SDVs. The results indicated that positive feelings of enjoyment predicted higher benefit perception and trust, whereas negative feelings predicted higher risk. Though the researchers did not specifically focus on perceived usefulness or perceived ease of use of SDVs, the study revealed valuable information regarding public perceptions of the technology.

Additional studies have explored the acceptance of SDVs using the TAM as well as other modified approaches (Böhm, Kocur, Firat, & Isemann, 2017; König, & Neumayr, 2017; Kyriakidis, Happee, & de Winter, 2015; Lee, et al., 2017; Madigan, et al., 2017; Nordhoff, van Arem, & Happee, 2016). Nuances in the factors explored in these studies help to expand the

DOI: https://doi.org/10.15394/jaaer.2020.1822

understanding of public perception of SDVs and which aspects impact willingness to accept the new technology. Results of all these studies resoundingly indicate perceived risk of safety negatively impacts users' attitudes towards SDVs. Furthermore, as hypothesized, environmental benefits, perceived usefulness, perceived ease of use and trust are all factors that positively impact user's willingness to accept SDVs.

Unmanned Aerial Vehicles

In the aviation industry, various studies have examined public acceptance of UAVs and their use in various applications. More than a million small UAVs have been registered for personal use in the US. Nearly half a million more are registered for commercial use (FAA, 2019). As the UAV industry grows and technological advancements reduce development costs, UAV applications become increasingly prevalent in many fields. From data gathering to policing to wildlife monitoring (Gonzalez, et al., 2016), UAVs provide considerable efficiencies to previously undermanned fields. Concurrently, public acceptance studies have explored the factors associated with intent to accept and use UAVs.

Aydin (2019) investigated the public's general acceptance of drones based on the Knowledge, Attitude and Practice (KAP) model using a quantitative survey. Though not specifically based on the TAM, this approach reviewed participants' perceptions of various UAV applications and associated perceptions of risk. Consistent with other studies, the results showed the public holds a general understanding of what UAVs are but are widely unaware of many uses and applications. Despite acknowledging potential benefits, results also indicated a significant concern regarding security and possible privacy violations that UAV applications present.

Additionally, Myers (2019) conducted a similar study on the acceptance of UAVs by employing a modified Behavioral Research Model. By combining portions of the existing TAM and theory of planned behavior (TPB), a new model, dubbed VMUTES for its creators, was developed for this study. Figure 3 depicts the theoretical framework and hypotheses presented in Myers' research. The VMUTES behavioral research model identifies the factors which influence a person's intent to use UAVs for data gathering. Adding factors of perceived risk and knowledge of regulations, Myers conducted an extensive analysis of data gathered via survey. The results of his study indicated positive relationships between perceived ease of use and behavioral intent as well as perceived usefulness and behavioral intent.

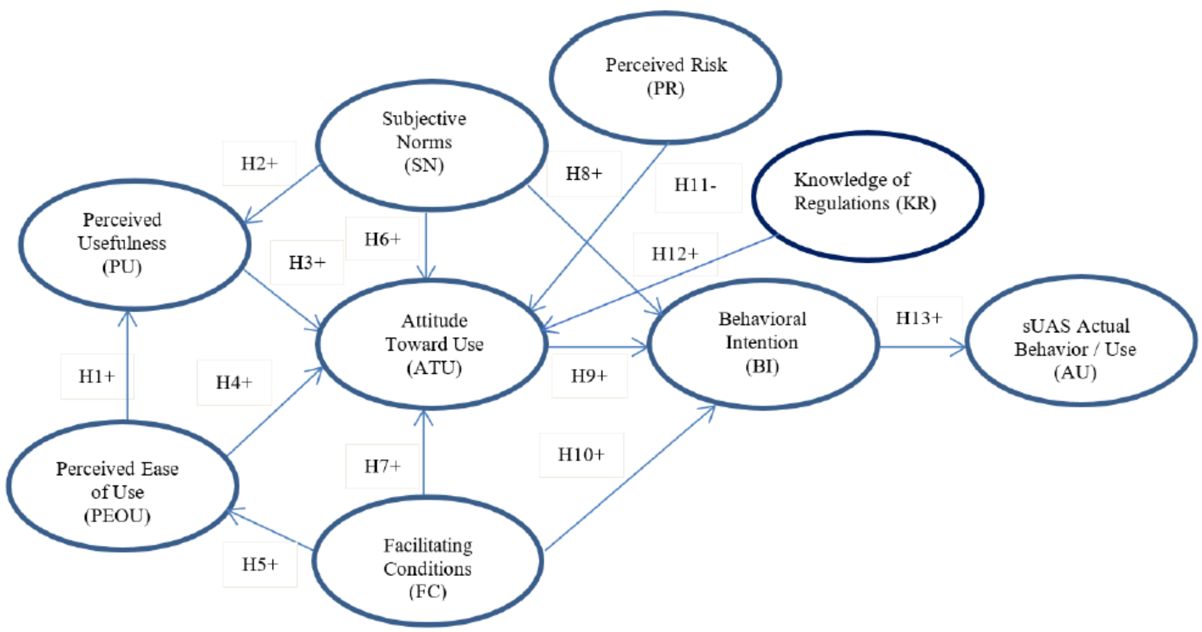

Figure 3. Proposed VMUTES model (Myers, 2019).

Yoo, Yu, and Jung (2018) conducted research to investigate what factors affect an individual's attitude toward a drone delivery service and their subsequent behavioral intent to use the technology. Consistent with similar studies, their research study utilized a survey tool to ask participants about factors that impact their perception of parcel deliveries by UAVs. They found speed, environmental friendliness and innovativeness positively affect a user's intent to use drones for delivery services. Additionally, performance risk and privacy risk were factors that negatively impacted a user's intent to use drones for delivery services. Further research has explored public acceptance of UAVs in society and their potential use in many applications (Boucher, 2016; Claesson, et al., 2016; Clothier, Greer, Greer, & Mehta, 2015; Rosenfeld, 2019).

Artificial Intelligence Decision-Making

To accurately comprehend the future of AI evolution, the pillars of notional intelligence must be defined. The Defense Advanced Research Projects Agency (DARPA) defines AI as the programmed ability to process information. Their definition further defines AI in four dimensions: perceiving, learning, abstracting and reasoning. DARPA's scale of notional intelligence is depicted in Figure 4. AI must be able to perceive the outside world and see what's going on, learn from the information gathered within an environment, abstracting that information or applying it to a higher level of processing, and finally it must be able to make decisions based on the information processed (Launchbury, 2017).

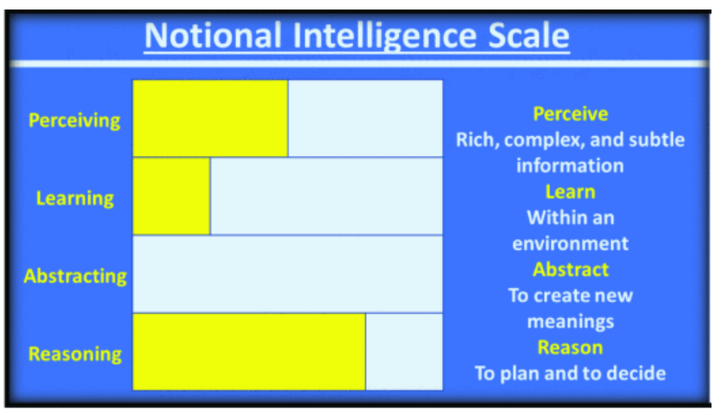

Figure 4. Four dimensions of AI (Stroup & Niewoehner, 2019).

Since Alan Turing's introduction to the Imitation Game, human-level intelligence in machines has become a technological singularity (Warwick & Shah, 2016). Once thought to be the demise of humanity, AI technology in present industries has lessened the burden of the operator and reduced the occurrence of human errors (Shimamoto, 2018). Instances in the aviation industry alone include facial recognition software in airports for customer identity verification, auto-pilot functions in aircraft to maintain level flight in lieu of the pilot, and Automatic Dependent Surveillance Broadcast (ADS-B) systems to assist in traffic situational awareness (McCallie, Butts, & Mills, 2011). These applications have helped to build trust in the technology and provide a foundation for further understanding and uses of AI advancements.

Research studies have investigated the acceptability and reliance of AI-based technologies for decision-making purposes. The literature indicates a prevalent concern regarding the transparency, accountability, and accuracy of AI-based systems. More specifically, the topic of machine learning is a common discussion among theorists. Probabilistic framework to this machine learning is comprised of models and predictions, scientific data analysis, artificial intelligence, cognitive science and robotics. The idea is machines can essentially be programmed to learn from observed data, make predictions about future data, and make decisions based on the analysis of these observations (Ghahramani, 2015).

Other articles highlight the concern over AI machine learning and margin of error. From a conceptual perspective, Berman (2018) evaluates the predictive analytics of the algorithmic models of AI technologies. Specifically, she investigates the level of accuracy achievable by AI systems and whether the margin of error is acceptable to replace humans for decision-making scenarios of national security and law enforcement. Based on her analysis, AI systems can consistently produce effective algorithmic predictions, which would yield significant benefits. However, she advises discretion and caution when introducing AI technology into the public sector for decision-making purposes due to the possibility of errors. This analysis provides insight into the lack of complete trust in autonomous systems.

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DOI: https://doi.org/10.15394/jaaer.2020.1822

Discussion and Conclusion

User acceptance of any new technology is critical to the implementation and prolonged use of the technology. As methods of transportation evolve with the introduction of SDVs and UAVs, the industry should wholly embrace and accept the technology for it to be successful (Aydin, 2019). Based on the widespread usage and proven success of the TAM, research studies have shown evidence of public acceptance of AI systems using various factors as predictors within a TAM. The literature review revealed an overall positive attitude towards applications of AI technology, including some instances of SDVs and UAVs. Specifically, research revealed environmental benefits positively impact a user's intentions to use SDVs along with perceived usefulness, perceived ease of use and perceived trust (Lee & Kolodge, 2019; Liu, Zhang, & He, 2019; Raue et al., 2019). The primary concerns identified include safety, security and error-free decision-making, which also impact the public's trust in these automated technologies and negatively affect a user's intentions to use SDVs (Aydin, 2019; Raue et al., 2019).

Using these research studies to assess the public's willingness to accept SFAs, it can reasonably be expected that environmental benefits, perceived ease of use, and perceived usefulness of SFAs will positively affect a user's willingness to accept and use this autonomous transportation system. Furthermore, as demonstrated in studies on SDV and UAVs, it can also be expected that safety risks will negatively affect a user's willingness to accept and use SFAs. In addition to safety risks, privacy and security are factors that contribute to the public's hesitance to accept various AI technologies. Trust in decision-making capabilities, to the level of DARPA's definition of AI, is critical for SFAs to be accepted by the public as a viable mode of autonomous transportation.

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