5th International Conference on Public Policy (ICPP5) July 5th–9th, 2021 – Barcelona, Spain

Investigating User Acceptance of Autonomous Systems: A Singapore Perspective on Governance using a modified UTAUT

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Thursday, July 8th 2021, 10:00 to 12:00

ICPP5 2021 - T07P18 / Evaluating policy responses to address digital disruption, industry transformations and workforce resilience

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Abstract - Autonomous systems that operate without human intervention by utilising artificial intelligence are a significant feature of the fourth industrial revolution. While the testing and use of autonomous systems such as driverless cars, unmanned drones and robots has become a major technological trend, we do not know much about the public's perceptions towards these systems. There has been a discussion of the benefits and risks of specific autonomous systems but more needs to be known about user acceptance of these systems. Reactions of the public, especially about novel technologies, can help policymakers understand the public's perspectives and needs better, and involve them in decision-making for governance and regulation of autonomous systems. Singapore has been a forerunner in developing AI-related systems. Given Singapore's suitability as a case, the study will examine the factors that influence the acceptance of autonomous systems by the public. The Unified Technology Adoption and Use Theory (UTAUT) is extended by introducing the role of government and incorporating a variable on trust in government. We use structural equation modelling for measuring the relationship between the variables and latent constructs to propose an autonomous systems acceptance model (ASAM). Using quantitative data from an online survey (n=500) in Singapore, we find that social influence and trust in government significantly and positively impact the behavioural intention to use autonomous systems. The variables of performance expectancy and effort expectancy are related positively to the intention to use the systems, and fear is related negatively. However, these variables have not

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been found to be significant. This study contributes to the literature on the governance of novel technologies and user acceptance of autonomous systems.

Keywords: Autonomous systems, governance, user acceptance, UTAUT, Singapore

1. Introduction

The proliferation of autonomous systems is a major technological trend with the fourth industrial revolution. Autonomous systems use artificial intelligence (AI) and operate without human intervention. Examples of autonomous systems include driverless cars, autonomous drones, exoskeletons, service robots, lethal autonomous weapons, and unmanned aircraft. High-income countries such as Netherlands, Singapore, Norway, United States, Finland, United Kingdom, Germany, South Korea, and Japan have already planned to adopt these systems in several sectors such as transportation, agriculture, defence, healthcare, manufacturing, and space exploration. Autonomous systems have significant benefits like economising time and cost and increasing efficiency in delivering public services. Service robots can reduce labour costs, work during unpopular hours and do repetitive tasks (Seyitoğlu & Ivanov, 2020). However, their operation has significant risks.

The risks of autonomous systems such as safety risks, privacy risks, liability risks, cybersecurity risks, job loss, and compromise on human interconnectedness have been discussed in various studies (Pettigrew et al., 2018; Raso et al., 2018; Taeihagh et al., 2021; Taeihagh & Lim, 2019). However, very little is known about the user acceptance of the domain of autonomous systems in a country or city. Studies have been conducted to examine the attitudes of people towards artificial intelligence and specific autonomous systems such as AVs, delivery robots, and drones (Abrams et al., 2021; Bansal & Kockelman, 2018; Kapser & Abdelrahman, 2020; H. Liu et al., 2019; Nordhoff et al., 2021; B. Zhang & Dafoe, 2020).

According to the 2020 Deloitte Global Automotive Consumer Study, 48 per cent of the consumers in the US are apprehensive about the safety of AVs. This number stands at 58 per cent for India and 35 per cent for China. The safety being threatened due to accidents involving AVs has been a concern for 72 per cent of the respondents in the Republic of Korea, 70 per cent in India, 68 per cent in the US and 55 per cent in China. Lee et al. (2015) have found through experiments that greater human-like appearance and autonomy of an AV was perceived to have more safety and trust in the system by the participants. The apprehensions about job losses with the advent of autonomous systems have been widely cited in the literature (Brougham & Haar, 2018; Pettigrew et al., 2018).

Public reactions about policy impacts of technology can help policymakers to address policy problems and questions by identifying demands of the public or involve the public in decision-making (Hisschemöller and Midden, 1999). This would provide a perspective from the public, which would be valuable for governments to configure their policy decisions—the perceptions of the public feed into the agenda-setting stage that would have a bearing on policy formulation. Studying public opinions is essential for various reasons. First, to have an insight into electoral politics and how policymakers would approach regulation and policy formulation (Burstein, 2003; B. Zhang & Dafoe, 2020). Second, the views of citizens about emerging technologies in their initial stages, and early in the policy cycle is a significant step due to the lessons learnt from reactions of the public for risk analysis and regulation (Brossard & Shanahan, 2007; H. Liu et al., 2019; Pidgeon, 1998).

In this paper, we investigate the user acceptance of autonomous systems in Singapore with the key research question: What factors impact an individual's behavioural intention to use autonomous systems in Singapore? While studies have examined user acceptance of separate autonomous systems such as autonomous vehicles, drones, and service robots (Abrams et al., 2021; Clothier et al., 2015; Kapser & Abdelrahman, 2020), no study focuses on the class of autonomous systems. We extend the Unified Technology Adoption and Use Theory (UTAUT) to introduce the importance of governance in gauging the intention to use autonomous systems. An inquiry into the acceptance of the class of autonomous systems will provide an insight into the acceptance of these systems by the public. Moreover, the lens of governance used will indicate the role of government in managing the risks of autonomous systems (Taeihagh, 2021). In addition, the context of Singapore is a notable case with the foremost ranking in the AI readiness index and has not been explored. The autonomous systems acceptance model in this paper will provide insights about the perceptions of the public in Singapore and their acceptance of autonomous systems. We study user acceptance in Singapore through an online survey to contribute to the emerging literature on acceptance of robots and autonomous systems by analysing the entire class of autonomous systems and bringing forth variables on trust in technology and government

The paper is structured as follows. Section 2 describes the theoretical framework for the study and the hypotheses for the autonomous systems acceptance model. Section 3 outlines the research methodology, including case selection, questionnaire, data, and methods for analysis. Section 4 elaborates on the results and findings. We discuss the findings study in section 5 before concluding and listing the study's limitations in section 6.

2. Theoretical framework and developing hypotheses

Literature exploring the acceptance of varied systems like driverless cars, service robots, healthcare robots, and autonomous drones have used models on technology acceptance to study the intention of use by individuals (Sung & Jeon, 2020). In this study, we define autonomous systems as “as powered physical systems that possess cognitive abilities through the computational capacity to self-direct themselves; they are aware of their surrounding environment, context and tasks allocated to them, operate without human intervention and generate outcomes by achieving sub-goals based on the ultimate goal in conditions that may or may not have been experienced previously (Bradshaw et al., 2013; Danks & London, 2017; Huang, 2007; Kaber, 2018; G. Liu et al., 2018; Pande & Taeihagh, Forthcoming; Veres et al., 2011). We use the UTAUT with an additional construct to examine the user acceptance for autonomous systems in Singapore.

2.1 Case Selection

For this study, the acceptance of autonomous systems would be gauged through a survey in Singapore. Singapore ranks first in the Government Artificial Intelligence (AI) readiness index and ranks high in the associated parameters[1] (Oxford Insights, 2019) of governance, infrastructure and data, government procurement, skills and education, and government and public services. Singapore has made strides in trials of autonomous vehicles since 2017 to advance the smart nation initiative (S. Tan & Taeihagh, 2021). Trials for autonomous shuttles, driverless taxis, mobility pods, driverless mobility scooters, and autonomous truck platooning system have been taking place since 2017 in Singapore (*ibid.*) Part of the smart nation initiatives are also robots and assistive technology in healthcare for the well-being of patients and the elderly (Smart Nation and Digital Government Office, 2021; Tan & Taeihagh, 2020).

[1] Governance (operationalised by the existence of data protection/ privacy laws and national AI strategy), Infrastructure and data (operationalised by data availability through open government data publication, government procurement of advanced technology products, data/AI capability in the government), Skills and education (operationalised by technology skills, private sector innovation capability, number of AI start-ups), Government and public services (operationalised by indicators on digital public services, effectiveness of government and importance of IT to government's vision of the future).

2.2 Unified Technology Adoption and Use Theory (UTAUT)

The adoption of autonomous systems would crucially depend on their 'acceptance' by the public. Theories such as the technology acceptance model (TAM) proposed by Davis (1986) for acceptance of information technology laid the foundation. Based on the theory of reasoned action[2] (TRA), the TAM suggests that using a new technology depends on the perceived ease of use and perceived usefulness (Fishbein & Ajzen, 1975). The TAM was too simplistic since it did not account for factors such as gender, age, experience, characteristics of the system, social influences and facilitating conditions that would influence the perceived usefulness and ease of use (Venkatesh & Davis, 2000; Venkatesh and Bala, 2008). Several modifications were made to TAM by including these factors, testing them empirically in different contexts and extending the constructs of perceived ease of use and perceived usefulness (Davis et al., 1989; Venkatesh & Bala, 2008; Venkatesh & Davis, 1996, 2000). The UTAUT was proposed with factors that determine the behavioural intention of users and the use of behaviour. The UTAUT described in figure 1 recognises four direct determinants and four moderating factors that affect the intention to use technology and, subsequently, usage behaviour factors (Venkatesh et al., 2003). They are 1) performance expectancy, 2) effort expectancy, 3) social influence and 4) facilitating conditions. The moderating factors are age, gender, experience, and voluntariness that influence the direct determinants.

[2]The Theory of Reasoned Action determines the intention of individuals to use a new technology/ product based on their attitude and subjective norms (Fishbein and Ajzen, 1975).

Figure 1:Technology Acceptance Model and the Unified Technology Adoption and Use Theory (Adapted from Venkatesh et al. (2003) *and* Lai (2017))

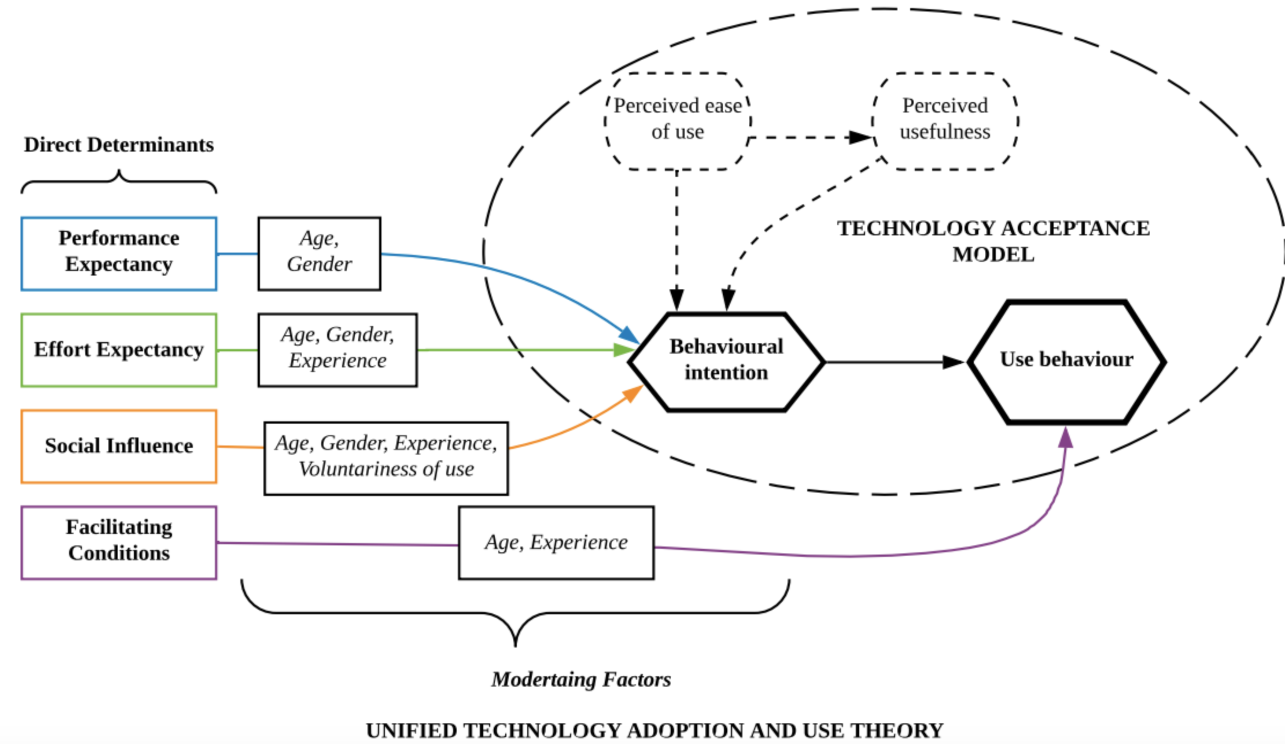


Table 1: Direct determinants of behavioural intention to use

Direct determinants of usage behaviour	**Meaning**
Performance expectancy	Defined as the extent to which technology will help the individual perform better (Venkatesh et al., 2003). It encompasses perceived usefulness, motivation to use, job-fit, relative advantage over previous systems and expectations of the outcome while using the technology. This indicates that knowledge and control of the system are included in this construct through the perceived usefulness.
Effort expectancy	Defined as the Ease of operating a system by the user (Venkatesh et al., 2003). It captures the perceived ease of use and complexity of a system.
Social influence	Defined as the degree to which an individual believes that others can use the system (Venkatesh et al., 2003). This captures the beliefs of people that others would benefit from the use of the system.
Facilitating conditions	Defined as the extent to which an individual believes that the supporting infrastructure is available to support the adoption of the system (Venkatesh et al., 2003).

The UTAUT is appropriate to gauge public perceptions of autonomous systems since it is meant for products to be introduced in the market (Lai, 2017) with an exhaustive set of determinants that affect the usage behaviour of individuals. However, from the factors discussed by Frewer (1999) and Slovic (1982), the fear or dread of using new technology is missing in the UTAUT. This is probably because UTAUT was conceived for information systems that do not pose risks to people's lives. This study uses behavioural intention to use as the main dependent variable that would represent user acceptance, similar to Kapser & Abdelrahman (2020). UTAUT will be the foundation of the theoretical framework, with suitable modifications. The TAM and its iterations, along with UTAUT, focus on the attitudinal factors of the public but do not include the role of government related to the management of emerging technologies. We have modified the model to incorporate governance implications on user acceptance of autonomous systems by adding trust in the government as an additional variable. According to UTAUT, facilitating conditions directly affect use behaviour and not behavioural intention to use, and can be excluded when examining the intention to use since this is beyond the scope of our research (Alaiad & Zhou, 2015; Van Belle & Cupido, 2013).

2.3 Developing hypothesis for Autonomous systems acceptance model (ASAM)

We have used the conceptualisations from the autonomous delivery vehicle acceptance model (ADV-AM) for measuring the latent constructs (Kapser & Abdelrahman, 2020). We add the variable related to trust in trust in government to handle autonomous systems in our model to propose an autonomous systems acceptance model (ASAM). The UTAUT constructs adopted for the ASAM model are described in Table 1. We present the hypotheses for this study in accordance with the literature on user acceptance for each of the constructs.

Table 2: Constructs and their measures

Constructs	Measures	Adapted Source
Performance expectancy (PE)	PE1: Autonomous systems would be useful in my daily life. PE2: I will be able to use autonomous systems for work. PE3: I will be able to control autonomous systems in daily life.	(Venkatesh et al., 2012)
Effort expectancy (EE)	EE1: Using autonomous systems would help me complete tasks quickly at work and at home. EE2: Using autonomous systems would increase my productivity at work. EE3: Using autonomous systems will help me save time and effort in my daily life. EE4: I would find autonomous systems easy to use. EE5: I would find it easy to interact with and have autonomous systems around me. EE6: I will become skilful at using autonomous systems with time at work. EE7: I will become skilful at interacting with autonomous systems with time.	(Venkatesh et al., 2012)
Social influence (SI)	SI1: I would like people who are important to me to use autonomous systems. SI2: People who influence my behaviour would like me to use and interact with autonomous systems.	(Venkatesh et al., 2012)
Fear/Dread (F)	F1: The advent of autonomous systems will pose a threat to my job. F2: Autonomous systems could be dangerous, resulting in injuries. F3: The operation of autonomous systems in Singapore would expose me to risks. F4: My interaction with autonomous systems could be risky and lead to death.	
Behavioural Intention to Use (BIU)	BIU1: I feel that in the future society will be dominated by robots. BIU2: I will make use of autonomous systems when they are available.	(Venkatesh et al., 2012) and authors

	BIU3: I will be comfortable with autonomous systems around me. BIU4: I will be comfortable with the operation of autonomous systems without any control over them.	
Trust in government (TG)	TG1: The government in Singapore will be able to manage the risks of autonomous systems. TG1: The government in Singapore is receptive to emerging technology. TG2: The government in Singapore understands the benefits of introducing autonomous systems. The government in Singapore understands the risks of introducing autonomous systems.	Authors

Performance expectancy: This is defined as the degree to which autonomous systems will assist the user to perform better. This construct enables measurement of perceived usefulness of the autonomous system for an individual, motivation to use the system, comparative advantage over previous systems and expectations of the results while using the system. Performance expectancy includes knowledge about the system. Performance expectancy, including perceived usefulness, has been found to significantly impact user acceptance for autonomous delivery vehicles (Kapser & Abdelrahman, 2020), and autonomous vehicles (Hegner et al., 2019; Madigan et al., 2017). Regarding performance expectancy, we hypothesise:

H1: Performance expectancy positively affects the behavioural intention to use autonomous systems.

Effort expectancy: This refers to the ease of operating a system by the user (Venkatesh et al., 2003). It captures the perceived ease of use and complexity of a system. Perceived usefulness and ease of use has a positive impact on the intention to use a robot (Schmidbauer et al., 2020). Effort expectancy has been found to positively affect the adoption of new technology like computer technology for various purposes (Casey & Wilson-Evered, 2012; Davis et al., 1989). Hence, we hypothesise:

H2: Effort expectancy positively impacts the behavioural intention to use autonomous systems.

Fear/dread: The concern of individuals towards AI or robotics, specifically concerning job loss, has been shown to have a negative impact on the acceptance of related technologies (Vu & Lim, 2021). Thus, we hypothesise:

H3: Fear negatively impacts behavioural intention to use autonomous systems.

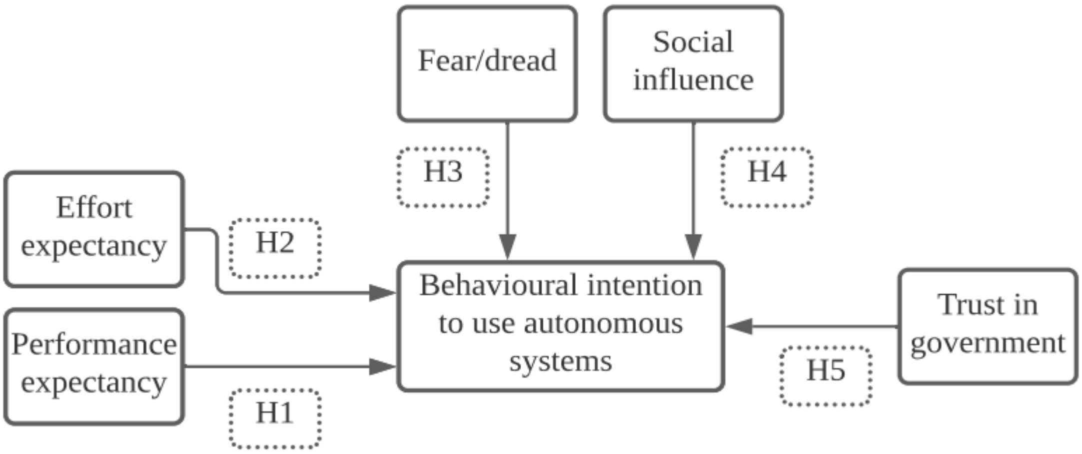
Social influence: Social influence has been found to positively impact behavioural intention to use automated transport (Madigan et al., 2017), autonomous delivery vehicles (Kapser & Abdelrahman, 2020) and automated vehicles (Kaur & Rampersad, 2018; Nordhoff et al., 2021; T. Zhang et al., 2020). Thus, the social network of an individual has an impact on the use of new technology. Accordingly, we hypothesise:

H4: Social influence positively impacts the behavioural intention to use autonomous systems.

Trust in government: People's perceptions towards emerging technology are often dependent on the trust in government (Siegrist & Cvetkovich, 2000). While many studies on user acceptance of autonomous cars have examined the role of trust in technology like an autonomous vehicle or automated shuttle (Bansal & Kockelman, 2018; Kaur & Rampersad, 2018; H. Liu et al., 2019; Nordhoff et al., 2021; Waung et al., 2021), no study has used trust in government as a variable that could impact the behavioural intention to use autonomous systems. It has been seen that the adoption of new technology depends positively on trust in the government. Thus, we hypothesise:

H5: Trust in the government to handle technology positively affects the behavioural intention to use autonomous systems.

Figure 2: Variables and hypothesised relationships in the autonomous systems acceptance model (ASAM)



3. Research Methodology

We executed an online survey in Singapore and analysed the data using structural equation modelling (SEM) to test the ASAM. The following sub-sections describe the questionnaire, data, and SEM.

3.1 Questionnaire design

To achieve the aims of the research, the survey instrument used was an online questionnaire. The questionnaire was designed with valid measures of the constructs listed in Table 1. The questionnaire was administered online with an average completion rate of 15-20 minutes. It had four parts with an information sheet and a form on consent to participate. Part 1 included questions about demographic characteristics (gender, age, highest education, employment status, monthly net income, and ethnicity (details in table 3). In addition, the respondents were also asked the source of information for developments in technology. Part 2 meant to gauge the knowledge and familiarity of respondents with autonomous systems.

Along with those questions, a vignette on autonomous systems was presented in this part. This comprised of a generic meaning of autonomous systems, countries adopting autonomous systems, and pictures of autonomous systems (a driverless car, an emotional companion robot, a manufacturing robot, an unmanned aircraft, and an autonomous assistive limb). Part 3 comprised questions to gauge the intention to use autonomous systems using a Likert scale of 5 points (1=strongly disagree, 2=disagree, 3=neutral, 4=agree, 5= strongly agree). Part 4 consisted of open-ended questions and multiple-choice questions on trust in government and willingness to participate in stakeholder engagements. A pre-test was conducted, and the questions were reviewed for confirming the face validity and content validity of the questions.

Table 3: Demographic characteristics and knowledge of autonomous systems among respondents

Characteristics	Items	Frequency (n=500)	Percentage
Gender	Male	255	51.0%
	Female	245	49.0%
Age (years)	20-24 (1)	32	6.4%
	25-34 (2)	68	13.6%
	35-44 (3)	77	15.4%
	45-54 (4)	111	22.2%
	55-64 (5)	112	22.4%
	65+ (6)	100	20.0%
Education level	Secondary school certificate or below (1)	88	17.6%
	High school degree (2)	74	14.8%
	University diploma (3)	71	14.2%
	Bachelor's degree (4)	184	36.8%
	Master's degree (5)	50	10.0%

	Doctorate (6)	5	1.0%
	No degree (7)	8	1.6%
	Others, please specify (8)	20	4.0%
Monthly income	SGD 2000 or less (1)	104	22.7%
	SGD 2001-SGD 5000 (2)	179	39.1%
	SGD 5001- SGD 8000 (3)	93	20.3%
	SGD 8001- SGD 11000 (4)	39	8.5%
	SGD 11001- SGD 14000 (5)	18	3.9%
	SGD 14001- SGD 17000 (6)	11	2.4%
	SGD 17001- SGD 20000 (7)	6	1.3%
	SGD 20001- SGD 23000 (8)	1	0.2%
	SGD 23001- SGD 26000 (9)	1	0.2%
	Above SGD 26000 (10)	6	1.3%
	Not applicable (11)	42	8.4%

3.2 Data

The study aims to gauge perceptions of people in Singapore, and hence we use quota sampling for the sample to be representative of the population in Singapore. The quota sampling was applied on two quotas--age and gender. These were based on data from the Singstat website provided by the Singapore Department of Statistics. The dataset comprises 500 complete responses, with adequate age and gender quotas that are representative of the population. The differences in percentage for gender are +/- 1 per cent and in age are +/- 2-3 per cent.

This research evaluates associations between latent constructs for which SEM is appropriate to study the information provided by the survey. SEM has the advantages of estimating coefficients in the model simultaneously, the ability to use latent variables and eliminating measurement error for obtaining more valid coefficients, and modelling multicollinearity (Dion, 2008). The statistical procedure enables to test hypotheses and directional patterns of relations between latent variables and observed variables (Hoyle, 1995; MacCallum & Austin, 2000). There are two stages involved in SEM (Nordhoff et al., 2021). The first stage is the confirmatory model analysis to determine the validity and reliability of the indicators. The second stage comprises the structural model to find the relationships between the latent and independent variables with the dependent variables.

4. Research Findings

4.1 Measurement model analysis

The data was tested for skewness and kurtosis and passed the test for normality. To assess the measurement model, we used Cronbach's alpha, comparative fit index (CFI), Tucker-Lewis index (TLI), and root mean square error of approximation (RMSEA) (table 4 and 5). The Cronbach's alpha to measure the internal reliability of constructs (Tarhini et al., 2016) ranged from 0.79 to 0.89, indicating high reliability of the measurements. Due to the low internal reliability, we excluded the following constructs from our model: EE4, F1, TG1 and BIU1. The RMSEA refers to the difference in the data and the expectation if the model is correct (Dion, 2008). The RMSEA value of 0.50 and CFI value of 0.95 for ASAM indicate that the model is a good fit (table 5). However, the value of TLI is slightly less than the standard (table 5. The $\chi 2$ test is considered in relation to the degrees of freedom and falls within the threshold level for ASAM (table 5). The standardised factor loadings were all above the threshold of 0.7 (Hair, 2009) from 0.72 to 0.87 (table 4).

Table 4: List of constructs, their factor loadings, mean, standard deviation and Cronbach's alpha

Construct	Item	Factor loadings	Mean	S.D	Cronbach's alpha

Performance expectancy (Q15-17) 15	PE1	0.7689388	3.838	0.8031476	**0.8235**
16	PE2	0.7298162	3.624	0.8649394	
17	PE3	0.8158445	3.6	0.8885827	
Effort expectancy (Q18-20, 23-25) 18	EE1	0.8345048	3.852	0.8120436	**0.8981**
19	EE2	0.7853362	3.8	0.8278712	
20	EE3	0.8103509	3.966	0.7196386	
23	EE5	0.7121566	3.572	0.8379859	
24	EE6	0.7250071	3.728	0.8529191	
25	EE7	0.7334095	3.85	0.7979809	
Fear 30	F2	0.7181295	3.3	0.937955	**0.8623**
31	F3	0.894902	3.142	0.9227888	
32	F4	0.8591735	2.916	0.9893947	
Social influence (Q26-27) 26	SI1	0.8706703	3.596	0.8355719	**0.7966**
27	SI2	0.7603395	3.484	0.8361473	
Trust in government 49	TG2	0.7120809	3.936	0.7161912	**0.8252**
50	TG3	0.8522277	3.848	0.7862139	
51	TG4	0.7959093	3.65	0.8514399	
Behavioural intention to use (Q 34-35) 34	BI2	0.8380508	3.698	0.8650391	**0.8248**
35	BI3	0.8207808	3.596	0.8379668	

Table 5: Fit indices for the model

Indices	**χ2**	**Degrees of freedom (df)**	**χ2/ df**	**RMSEA**	**TLI**	**CFI**
Thresholds			Between 1 and 3	≤0.070	≥0.95	≥0.95
Results	487.348	217	2.24	0.050	0.945	0.955

4.2 Structural model analysis

We found a positive relationship of performance expectancy, effort expectancy, social influence, and trust in government with behavioural intention to use autonomous systems. This is in line with our hypotheses. However, only social influence and trust in government were significant at a 1% significance level. Thus, H4 and H5 have been confirmed in ASAM. This implies that people in Singapore strongly believe that the use of autonomous systems can benefit their peers and relatives. The trust in the government to adopt autonomous systems safely and handle the risks from their operation also impacts the behavioural intention to use them for people in Singapore. We find that amongst the independent variables, age and education are significant at a 10% significance level with a positive relationship to behavioural intention to use autonomous systems.

Table 6: Results of hypothesised relationships in ASAM

Hypothesis	Path	Effect	Coefficient	p-value
H1	PE→BIU	positive	0.2981096	0.308
H2	EE→ BIU	positive	0.28418	0.363
H3	F→BIU	negative	-0.0488415	0.201
H4	SI→BIU	positive	0.2487885	0.002***
H5	TG→BIU	positive	0.1503215	0.002***

*** significant at 1% significance level

Table 7: Results of independent variables in ASAM

Path	Coefficient	p-value
Gender→BIU	0.0351146	0.351
Age→ BIU	0.0592479	0.081**
Education→ BIU	0.0632279	0.065**
Monthly income→ BIU	0.0109001	0.803
Heard of autonomous systems→ BIU	-0.0258976	0.499

**significant at 10% significance level

5. Discussion and limitations of the study

This study finds and elucidates the factors that affect the behavioural intention to use autonomous systems in Singapore by proposing the ASAM. The responses of individuals who took the survey indicate a fairly positive attitude towards behavioural intention to use autonomous systems, with the means of the various constructs being more than 3, the mid-point of the Likert scale (except fear which has a negative relation with behavioural intention to use autonomous systems). This is different from the usual perspective of people, as noted by Liu et al. (2019) of having a neutral stance towards emerging technologies because they need time to form an opinion. In the survey, more than half of the respondents (66.7 per cent) had heard of autonomous systems before they were presented with the information on them in the questionnaire. This can be attributed to the technological advancement in Singapore and its position as the second in digital competitiveness after the United States (Chang, 2020).

Regarding the variables in ASAM, we find that social influence and the additional construct of trust in the government has a significant impact on the behavioural intention to use autonomous systems, similar to the findings for automated vehicle acceptance in China (T. Zhang et al., 2020). According to the magnitude of coefficients, performance expectancy and effort expectancy have the highest impact on behavioural intention to use autonomous systems, followed by social influence, trust in government, and fear. However, performance expectancy, effort expectancy and fear did not have a significant impact on the model. This is different from studies on acceptance of automated road transport systems and autonomous delivery vehicles for which performance expectancy has been a positive and significant on behavioural intention to use (Kapser & Abdelrahman, 2020; Madigan et al., 2017). However, the results on effort expectancy—of a positive but insignificant relationship to user acceptance are in concordance with those studies. A possible reason for this could be that ASAM incorporates all types of autonomous systems, due to which it is difficult to separate performance and effort expectancy across varied systems.

In the results for independent variables included in ASAM, age and education have been found to be the key variables that affect user acceptance.

The study has some limitations. First, since autonomous systems have not been introduced, the perceptions might not give a clear indication of their adoption by the public, especially because 19 per cent of respondents had not heard of autonomous systems, around 14 per cent were not sure if they had, and almost 70 per cent of the respondents in our survey had not interacted with autonomous systems. Second, the survey was conducted online, which means there might have been some self-selection of respondents who use the internet.

6. Conclusion and future research

This study highlights that social influence and trust in government are the most significant variables in the ASAM to impact behavioural intention to use autonomous systems in Singapore. This is indicative of the role of the government in the adoption of autonomous systems in Singapore. The factors of age and education of the potential users of the systems will be crucial to consider the introduction of autonomous systems in Singapore and their governance. While behavioural intention to use might not necessarily imply acceptance and use of the systems, the perceptions from this study help draw insights about the keenness of people in Singapore to adopt these systems. Future research can focus on using the ASAM to study user acceptance in different jurisdictions and compare the factors influencing user acceptance.

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