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Exploring customer adoption of autonomous shopping systems

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ABSTRACT

Autonomous technology is on the rise, allowing customers to delegate shopping tasks and decisions to such artificial intelligence-based systems. However, trust and privacy issues are impeding the adoption of such technology. This study examines the factors affecting the adoption of autonomous shopping systems. A conceptual framework is developed by adding trust and moderating variables of privacy concern to the UTAUT model. Using a quantitative research design, data is collected from 454 respondents and analysed using covariance-based structural equation modelling. Results show that performance expectancy, effort expectancy, social influence, and facilitating conditions positively impact perceived trust in autonomous shopping systems. Privacy concern as a moderator dampens the positive relationship between performance expectancy and perceived trust. Also, privacy concerns dampen the positive relationship between social influence and perceived trust. This study is one of the first to empirically examine customers' autonomous shopping system intention by revising the UTAUT with trust and privacy concerns. These findings generate valuable insights into an under-researched area of customer behaviour and artificial intelligence.

1. Introduction

The retailing landscape has changed significantly with technological advancements (Shankar et al., 2020). Customer experience changes as new technologies change how customers interact with the seller, how shopping is done, and overall convenience (Grewal et al., 2020). Artificial intelligence (AI) advancements have led to the development of autonomous systems that are changing the way customers shop (Grewal and Roggeveen, 2020; Meske et al., 2020). An autonomous shopping system is one such AI-based system (Sharma et al., 2022a).

There is increased interest by researchers and practitioners in understanding AI (Kankanamge et al., 2021; Liew and Tan, 2021; Sun et al., 2020). De Bellis and Johar (2020) define autonomous shopping systems as "technology to which consumers can delegate substantial parts of the shopping process, including shopping decisions and tasks." For such systems to accurately predict and make purchases on behalf of customers, large amounts of personal data are needed from customers. For convenience and personalised service, many customers are willing to share such information (Aguirre et al., 2015). However, customers remain concerned about their data (Inman and Nikolova, 2017; Okazaki et al., 2020). This lack of trust and privacy concerns will likely impede the adoption of AI-based autonomous shopping systems. Researchers have focused a lot on privacy concerns over the years (Lim, 2018; Prokofieva and Miah, 2019; Wahlstrom et al., 2020). However, privacy research tends to vary across different contexts and retailers (Okazaki et al.,

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2020), thus driving more research as innovative technologies are introduced.

Based on the above discussion relating to the gaps in the literature, the following research questions (RQ1) are outlined. **RQ1.** What factors affect customers' trust in autonomous shopping systems? **RQ2.** Do customers' privacy concerns moderate the relationships between UTATU constructs (effort expectancy, performance expectancy, facilitating conditions, and social influence) and trust? **RQ3.** Does trust influence customers' autonomous shopping adoption intention? The data collected from 454 customers will be used to address these research questions by performing covariance-based structural equation modelling.

This study will make the following contributions. First, it is one of the first to empirically examine how customers' trust and privacy concerns impact their adoption of autonomous shopping intentions. By doing so, this study addresses the research agenda proposed by De Bellis and Johar (2020). Second, based on Tamilmani et al. (2020)'s recommendation, this study adds trust as a new variable in the UTAUT model. This addition allows for new relationships to be explored. Third, this study adds privacy concern as a moderating variable between the UTAUT variables (performance expectancy, effort expectancy, social influence, and facilitating conditions) and customers' intention to adopt autonomous shopping intention. While studies have modelled privacy concerns directly related to behavioural intention, the moderating impact on the UTAUT variables has not been examined.

2. Theoretical foundation

2.1. Unified theory of acceptance and use of technology (UTAUT)

The UTAUT model is a technology acceptance model proposed by Venkatesh et al. (2003). Since then, it has been extensively used to study the intention to adopt information systems and actual behaviour (Sharma et al., 2022a; Sharma et al., 2020b; Sharma et al., 2020c). The theory combines eight technology acceptance models, namely; social cognition theory models, the combined Technology Acceptance Model (TAM) and Theory of Planned Behavior (TPB) model, innovation diffusion theory, the model of Personal Computer (PC) utilisation, the TPB, the motivational model, Theory of Reasoned Action (TRA), and the TAM model. This combination derives a unified technology acceptance model applicable across different cultures and countries and can predict behavioural intention with a variance of around 70 % (Sharma et al., 2020b; Singh, 2020).

The UTAUT framework consists of four antecedents to behavioural intention. These are effort expectancy, performance expectancy, facilitating conditions, and social influence. The behavioural intention then acts as an antecedent to actual behaviour. The reason for adopting the UTAUT model in this study is as follows. First, due to the incorporation of eight technology acceptance models, it is considered the most comprehensive model is predicting behavioural. Second, the model has been shown to possess superior predictive power in the information technology context. Third, the model is known for its parsimony, simplicity, and robustness (Venkatesh and Goyal, 2010; Venkatesh et al., 2012). As such, this model seems to be the most relevant for this research.

2.2. Conceptual framework and hypotheses development

Performance expectancy is defined as the extent to which a person believes that using a new system will help them attain gains (Venkatesh et al., 2003). In the context of an autonomous shopping system, this would be the benefit of using this system in terms of convenience and increased productivity. Customers are eager to adopt new technology to reduce effort and increase time savings (Alalwan, 2020; Fernandes and Oliveira, 2021; Zhao and Bacao, 2020). Studies have confirmed the opposite positive relationship between trust on performance expectancy (Alalwan et al., 2017; Baganzi and Lau, 2017; Hanafizadeh et al., 2014). However, little research has been done to investigate the relationship between performance expectancy on trust. Loureiro et al. (2018) found that the relationship between performance expectancy and trust is insignificant in online fashion websites. In the context of an autonomous shopping system, customers will more likely trust such systems if their use yields benefits. Therefore, it is hypothesised that:

H1. Performance expectancy positively influences consumers' trust in autonomous shopping.

Effort expectancy is the ease of using a system (Venkatesh et al., 2003). Customers are motivated to accept new technology that requires little effort to learn and is easy to use (Alalwan, 2020). Studies have confirmed that trust positively impacts effort expectancy (Lee and Song, 2013). However, little empirical evidence is available on the influence of effort expectancy on trust. Customers who find autonomous shopping systems easy to use and lack complexity would trust the system. This has been confirmed by Chang et al. (2017) in the context of social networking websites. The study found that customers were more trusting of social networking sites that were easy to use (Chang et al., 2017). Zheng et al. (2012) also found that ease of use positively influenced trust formation in mobile commerce. Therefore, it is hypothesised that:

H2. Effort expectancy positively influences consumers' trust in autonomous shopping.

Social influence is referred to as the influence of significant others (friends, family, peers, colleagues) on a person's attitude and behaviour (Venkatesh et al., 2003). Research has established that social influence is crucial in influencing customer actions (Lejealle et al., 2021; Naeem, 2021). According to the study by Gursoy et al. (2019), social influence is a critical factor influencing customers' adoption of service delivery AI. Similar results have been found by Lin et al. (2020) with AI-driven robots in the hospitality industry. Social influence profoundly impacts the level of trust an individual has towards a system. Baabdullah et al. (2019) found that social influence leads to trust formation for customers when considering adopting Mobile Social Network Games (M−SNGs). Shareef et al.

(2017) also found that social influence positively influences consumer trust in mobile marketing. Similar results were found by Chang et al. (2017) with social networking sites. These results imply that the reviews, comments, and feedback relating to using an autonomous shopping system from individuals close to the customer can influence trust towards the system. Therefore, it is hypothesised that:

H3. Social influence positively influences consumers' trust in autonomous shopping.

Facilitating conditions refer to the availability of support services and technical infrastructure for systems (Venkatesh et al., 2003). Facilitating conditions profoundly affect technology adoption (Lau et al., 2020; Wong et al., 2020; Zhou et al., 2020). Zhou et al. (2020) found that facilitating conditions were a key factor in self-service delivery adoption. Kaye et al. (2020) found that facilitating conditions affected customers' adoption of autonomous driving vehicles. Similar results were found by Kapser and Abdelrahman (2020) and Lu et al. (2019) in the context of AI adoption. In the context of an autonomous shopping system, customers are more likely to trust such systems where there are support services (e.g., live chat and informative websites) are available to assist potential users of such systems. This will increase their confidence in the use of autonomous shopping systems. Therefore, it is hypothesised that:

H4. Facilitating condition positively influences consumers' trust in autonomous shopping.

Privacy refers to an individual's right to control the collection and use of personal information, both non-digital and digital (Merhi et al., 2019). This is the right to ensure no disclosure of personal information without prior approval. Studies on privacy have increased, particularly concerning AI (Cheng et al., 2021; Zarifis et al., 2020). Trust is a crucial element in the relationship between a person and an automated person (Hengstler et al., 2016). Consequently, privacy is critical to trust, as customers are concerned about their personal information control. Studies have shown that trust can alter the relationship between convenience in the context of AI (Ferrario et al., 2019; Siau & Wang, 2018). As such, the benefits of autonomous shopping systems lead to trust formation. However, this is weakened when customers are concerned with privacy issues concerning their personal data. Therefore, the following hypothesis is proposed.

H5a. The relationship between performance expectancy and consumers' trust in autonomous shopping is weaker with customers with high privacy concerns.

When intending to use an autonomous shopping system, customers would be concerned about the ease of keeping their personal data secure. According to Tan et al. (2012), despite privacy concerns not directly affecting users' behavioural intention, it is mediated by perceived ease of use in the context of social networking websites. In mobile-commerce Zheng et al. (2012) found that ease of use positively influences trust formation. Similarly, Chang et al. (2017) also found that ease to use and lack of complexity lead to trust in the system. Also, ease of use has decreased individuals' privacy concerns (Al-Khalaf and Choe, 2020; Zarifis et al., 2020). Customers should not require high skills, technical ability, or effort to ensure their data privacy when using autonomous shopping systems. Therefore, the following is hypothesised:

H5b. The relationship between effort expectancy and consumers' trust in autonomous shopping is weaker with customers with high privacy concerns.

Due to artificial intelligence relying on a large amount of data, trust becomes important for customers (Dwivedi et al., 2021). While the direct relationship between social influence and intention behaviour has been explored by many studies (Lejealle et al., 2021; Naeem, 2021), few have found that social influence also led to trust formation (Baabdullah et al., 2019; Li et al., 2008). However, this relationship has not been examined when moderated by privacy concerns. The study by Ozturk et al. (2017) found privacy concerns to impact trust negatively. Xu (2019) also found that privacy concerns relating to health informatics negatively impacted trust formation. This implies that despite social influence positively influencing customers' intention to adopt autonomous shopping systems, this relationship is weakened when customers have privacy concerns about disclosing personal information. Therefore, it is hypothesised that:

H5c. The relationship between social influence and consumers' trust in autonomous shopping is weaker with customers with high privacy concerns.

Customers intending to use autonomous shopping systems are concerned about the system's facilitating conditions to protect their personal data (Wang and Herrando, 2019). Trust seals (e.g., TRUSTe or VeriSign) can improve customers' trust based on the trust transfer theory. (Miltgen and Smith, 2015). Systems with seal certification, strong privacy compliance rules, and procedures make potential users feel at ease (Widjaja et al., 2019). Privacy issues have been found to decrease trust and information disclosure (Inman and Nikolova, 2017). Customers will find it difficult to trust autonomous shopping systems if they perceive that the system does not have the technical infrastructure to protect their information privacy. Therefore, it is hypothesised that:

H5d. The relationship between facilitating conditions and consumers' trust in autonomous shopping is weaker with customers with high privacy concerns.

Researchers have focused much attention on trust with AI (Glikson and Woolley, 2020; McLean et al., 2020; Pillai et al., 2020). According to Lee and See (2004), trust is the belief that an agent will help accomplish goals when faced with vulnerability and uncertainty. Trust has been found to be a key antecedent of behavioural intention (Du et al., 2021; Shareef et al., 2021; Song and Luximon, 2021). It is a key factor driving AI's acceptance and adoption (Glikson and Woolley, 2020). Cha (2020) found a positive relationship between perceived trust and intention to use robot-serviced restaurants. According to the study by Dirsehan and Can (2020), trust affects autonomous vehicle adoption. Similar results were found by Park (2020) and Cameron et al. (2021) with AI-based systems adoption. In the context of autonomous shopping systems, customers' trust will likely increase their motivation to adopt the system. Therefore, it is hypothesised that:

H6. Trust in autonomous shopping positively influences customers' autonomous shopping intention.

Based on the above hypotheses, we develop the conceptual framework for this study, illustrating the proposed relationships between variables (Fig. 1).

3. Research methodology

3.1. Procedure and participants

A pilot study was conducted before the full survey with ten post-graduate students at the University of the South Pacific. This resulted in small changes being made to the wordings of a few items to enhance readability. Following this, a sponsored advertisement was placed on Facebook to circulate the link to the online survey. Facebook was selected as it is the most popular social networking site in Fiji (Sharma et al., 2020a). The survey was hosted on the popular online survey development website, SurveyMonkey. Prior studies have adopted similar methods of research (Sharma et al., 2021a; Sharma et al., 2021b; Singh et al., 2021).

3.2. Measures

A 7-point Likert scale was used due to its reliability in capturing valuable data from the survey participants (Chen et al., 2011). All scales employed in this study have been sourced from prior studies. These scales have been modified to match the context of this study (Table 1). The detailed scales, together with their sources, can be found in Appendix A.

Statistical Package for the Social Sciences (SPSS) and IBM SPSS Amos was used to perform data analysis. This study uses covariance-based structural equation modelling (CB-SEM) to test the relationships proposed in the conceptual framework. CB-SEM is considered appropriate for this study as it allows the linkage between research philosophy, theories, and empirical data (Bagozzi and

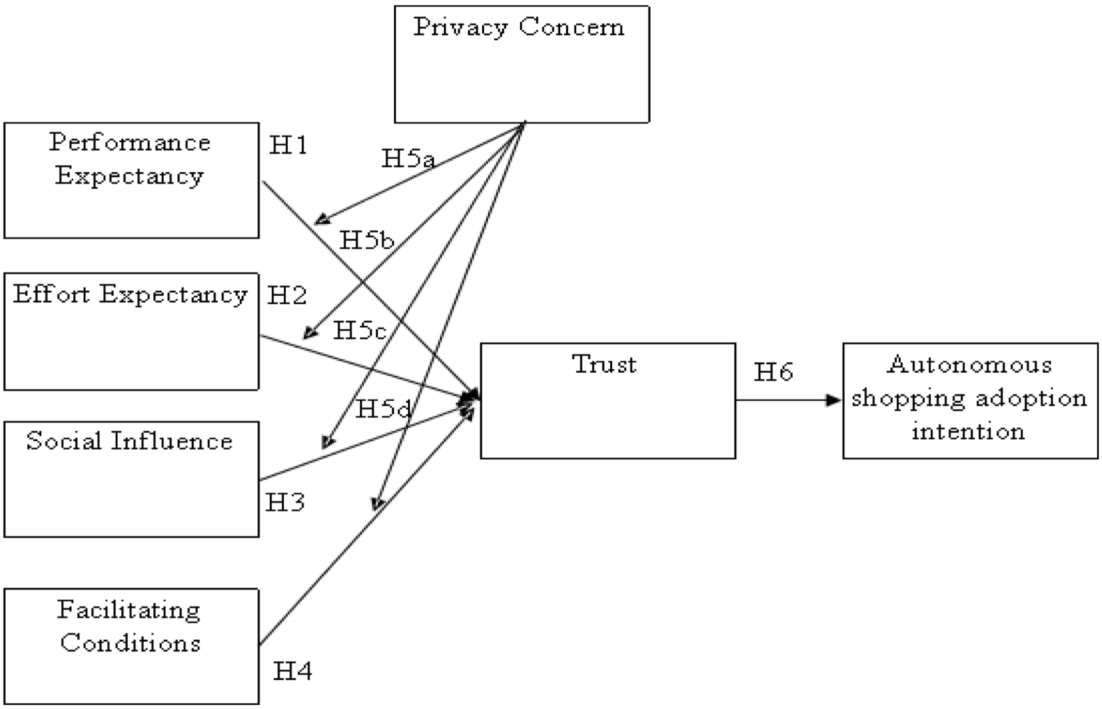

Fig. 1. Conceptual Framework.

Table 1
Demographic Profile.

Gender	N	%
Male	250	55.07
Female	191	42.07
Do not wish to include	13	2.86
Age		
18–25 years	108	23.79
26–30 years	151	33.26
31–40 years	113	24.89
41–50 years	68	14.98
50 years and above	2	0.44
Do not wish to include	12	2.64
Income		
I do not earn an income	53	11.67
Under $15,000	109	24.01
$15,000-$29,999	93	20.49
$30,000-$44,999	74	16.3
$45,000-$59,999	43	9.47
$60,000-$74,999	41	9.03
$75,000-$89,999	39	8.59
$90,000 +	2	0.44

Yi, 2012). It has a popular method employed by many studies (Sharma and Singh, 2022; Sharma et al., 2021a,b,c; Sharma et al., 2022b).

Four hundred fifty-nine participants responded to the online survey. The examination was conducted for data containing unengaged responses, normality of distribution, and issues relating to multicollinearity. From this, five responses were removed from the dataset as their Z-score values identified these responses as outliers. That is, their Z-score values exceeded the limit of 3.29, as Tabachnick et al. (2007) suggested. The remaining 454 were used for further analysis. Data was found to be normally distributed as it passed the kurtosis and skewness tests Hair et al. (2010). Confirmation of the absence of multicollinearity issues was ascertained by the variance inflation factors and tolerance values being within the recommended range.

3.3. Demographic profile of respondents

The demographic profile for the participants of this study is presented in Table 2. 250 respondents (55.07 percent) were males while 191 respondents (42.07 percent) were females while the remaining 13 respondents (2.86 percent) did not wish to indicate their gender. 108 respondents (23.79 percent) were between the ages of 18 to 25, 151 respondents (33.26 percent) were between the ages of 26 to 30, 113 respondents (24.89 percent) were between the ages of 31 to 40, 68 respondents (14.98 percent) were between the ages of 41 to 50, 2 respondents (0.44 percent) were 50 years and above. The remaining 12 respondents (2.64 percent) did not wish to indicate their age. 53 respondents (11.67 percent) did not earn an income, 109 respondents (24.01 percent) earned under $15,000, 93 respondents (20.49 percent) earned between $15,000 to $29,999, 74 respondents (16.3 percent) earned between $30,000 to $44,999, 43 respondents (9.47 percent) earned between $45,000 to $59,999, 41 respondents (9.03 percent) earned between $60,000 to $74,999, 39 respondents (8.59 percent) earned between $75,000 to $89,999 while the remaining 2 respondents 0.44 percent earned more than $90,000.

Table 2
Discriminant validity.

	CR	AVE	MSV	MaxR(H)	PFE	EFE	SIF	FLC	ASI	PRT	PVC
PFE	0.91	0.71	0.51	0.91	**0.84**						
EFE	0.91	0.71	0.51	0.91	0.41***	**0.84**					
SIF	0.91	0.77	0.51	0.91	0.40***	0.13***	**0.88**				
FLC	0.86	0.72	0.59	0.87	0.17***	0.28***	0.21***	**0.82**			
ASI	0.92	0.75	0.43	0.94	0.32***	0.38***	0.11***	0.42***	**0.86**		
PRT	0.94	0.79	0.59	0.95	0.17***	0.18***	0.29***	0.37***	0.26***	**0.89**	
PVC	0.8	0.78	0.05	0.85	0.23***	0.11*	0.12***	0.16**	0.12*	0.23***	**0.76**

Note: The boldfaced diagonal elements are the square root of the variance shared between the constructs and their measures. Off-diagonal elements are the correlations between constructs. *** $p < 0.001$. PFE = Performance expectancy; EFE = Effort expectancy; SIF = Social influence; FLC = Facilitating condition; PRT = Perceived trust; PVC = Privacy concern; ASI = Autonomous shopping intention; CR = Composite Reliability; AVE = Average Variance Extracted; MSV = Maximum Shared Variance; MaxR(H) = Maximum Reliability. Significance of Correlations: † $p < 0.100$; * $p < 0.050$; ** $p < 0.010$; *** $p < 0.001$.

4. Results

4.1. Common method bias

To ensure that this study's results were not impacted by common method bias (CMB), a common latent factor was used to investigate this. The variance was found to be 30.26 percent. This confirms that CMB's results are not impacted, as 30.26 is below the threshold of 50 percent suggested by Podsakoff et al. (2003).

4.2. Measurement model

Composite reliability for all factors was more than the recommended 0.70. The internal consistency of the variables used in the study was confirmed by computing the Cronbach alpha test. The following results were revealed: performance expectancy (0.906), effort expectancy (0.905), social influence (0.907), facilitating conditions (0.857), privacy concern (0.891), trust (0.934), and autonomous shopping intention (0.919). The results highlight high internal consistency for all variables and its appropriateness to be used in further analysis. Discriminant validity was confirmed (see Table 3 for detailed results). The model fit was examined. The following results were found: [$x^2/df = 2.86$, $CFI = 0.90$; $GFI = 0.91$; $TLI = 0.92$; $RMSEA = 0.03$]. These values depict a good model fit as the values meet the recommended values suggested by Hair et al. (2006).

4.3. Structural model

Following the successful results from the measurement model test, the structural model is examined to test the hypotheses formulated at the start of this study. The following model fit figures were obtained. [$x^2/df = 3.04$, $CFI = 0.926$; $GFI = 0.911$; $TLI = 0.931$; $RMSEA = 0.029$]. This indicated a good model fit for the structural model. Subsequently, analysis was performed to test the hypothesised relationships.

First, the direct relationships were examined. Then, the moderating effects of PVC were examined. Specifically, the interaction effect of PFE × PVC, EFE × PVC, SIF × PVC, and FLC × PVC.

The direct relationship result found PFE ($\beta = 0.24$, $P < 0.001$), EFE ($\beta = 0.19$, $P < 0.001$), SIF ($\beta = 0.19$, $P < 0.001$), and FLC ($\beta = 0.38$, $P < 0.001$) to positively influence PTR. PTR ($\beta = 0.69$, $P < 0.001$) was found to influence ASI positively. Therefore, H1, H2, H3, H4, and H6 were supported. Looking at the moderating effect of PVC. PVC dampens the positive relationship between PEF and PRT (see Fig. 3). Also, PVC dampens the positive relationship between SIF and PRT (see Fig. 4). Therefore, H5a and H5c are supported.

The predictive power of the model is measured using the R^2 value. The R^2 for trust was 52 percent, while autonomous shopping intention was 41 percent. Both met the minimum threshold of 40 percent Straub et al. (2004). The results are illustrated below (Fig. 2).

Table 3
Measurement of constructs.

Variable	Measurement items	Model and item indices	
		SL	SMC
Performance Expectancy	PFE1	0.90	0.80
	PFE2	0.86	0.75
	PFE3	0.83	0.69
	PFE4	0.78	0.60
Effort Expectancy	EFE1	0.79	0.62
	EFE2	0.84	0.71
	EFE3	0.88	0.78
	EFE4	0.85	0.72
Social Influence	SIF1	0.86	0.74
	SIF2	0.91	0.83
	SIF3	0.86	0.74
Facilitating Condition	FLC1	0.74	0.55
	FLC2	0.83	0.69
	FLC3	0.88	0.78
Privacy Concerns	PVC1	0.87	0.76
	PVC2	0.87	0.76
	PVC3	0.81	0.67
Trust	PRT1	0.83	0.68
	PTR2	0.91	0.84
	PRT3	0.94	0.88
	PRT4	0.86	0.75
Autonomous Shopping Intention	ASI1	0.88	0.77
	ASI2	0.94	0.88
	ASI3	0.84	0.71
	ASI4	0.80	0.64

4.4. Discussion

The proposed relationship of performance expectancy positively influencing consumers' trust in autonomous shopping was confirmed by this study. While this relationship has been largely unexplored, Loureiro et al. (2018) found that the relationship between performance expectancy and trust is insignificant in online fashion websites. The findings of this study contradict the study by Loureiro et al. (2018). Despite this, the findings imply that customers are more trusting of an autonomous shopping system that can yield benefits.

This study also confirmed the positive relationship between effort expectancy on consumer's trust in autonomous shopping. Studies have confirmed that trust positively impacts effort expectancy (Lee and Song, 2013). However, little empirical evidence is available on the influence of effort expectancy on trust. Similar findings were derived by Chang et al. (2017) on social networking websites. This result implies that customers are more likely to trust autonomous shopping systems perceived to be easier to use.

Empirical results from this study have confirmed that social influence positively influences consumers' trust in autonomous shopping. Studies have confirmed the relationship between social influence and behavioural intention (Lejealle et al., 2021; Naeem, 2021). Baabdullah et al. (2019) also found that social influence leads to trust formation for customers when considering adopting Mobile Social Network Games (M−SNGs). Chang et al. (2017) and Shareef et al. (2017) found results similar to this study. This finding implies that customers are more willing to adopt an autonomous shopping system based on their close friends and family's recommendations.

This study's empirical results confirmed the hypothesis that facilitating conditions positively influence consumers' trust in autonomous shopping. Much of the research has shown that facilitating conditions positively influence behavioural intention (Lau et al., 2020; Wong et al., 2020; Zhou et al., 2020). However, the relationship between facilitating conditions impacting trust perception remains unexplored. This finding highlights that customers are more likely to trust autonomous shopping systems when support services (e.g., live chat and informative websites) are available to assist potential users of such systems.

The moderation analysis confirmed that the relationship between performance expectancy and consumers' trust in autonomous shopping is weaker with customers with high privacy concerns. Despite this exact relationship being unexplored, studies have shown that trust can alter the relationship between convenience and adoption intention in the context of AI (Ferrario et al., 2019; Siau and Wang, 2018). This result implies that customers' privacy concerns weaken the increased intention to adopt autonomous shopping systems due to their perceived benefits.

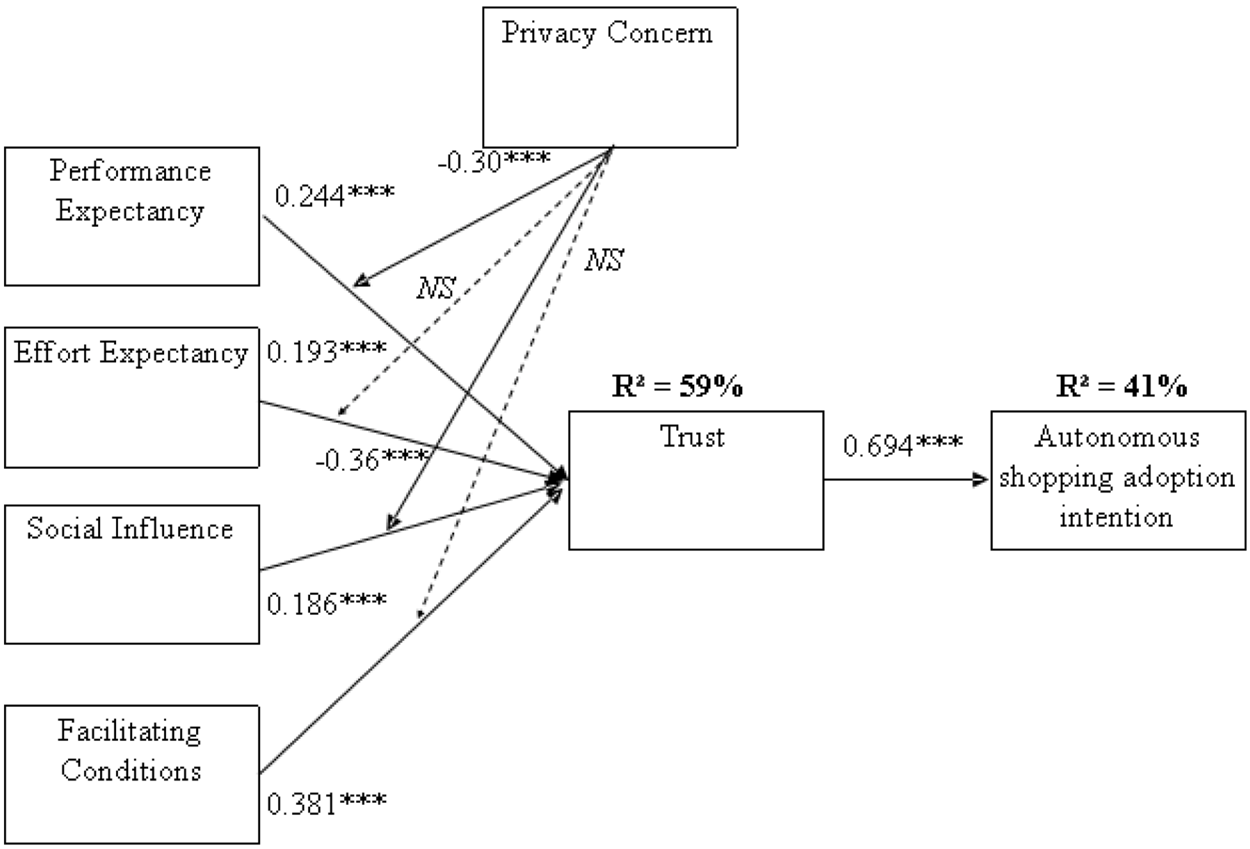

Fig. 2. Result.

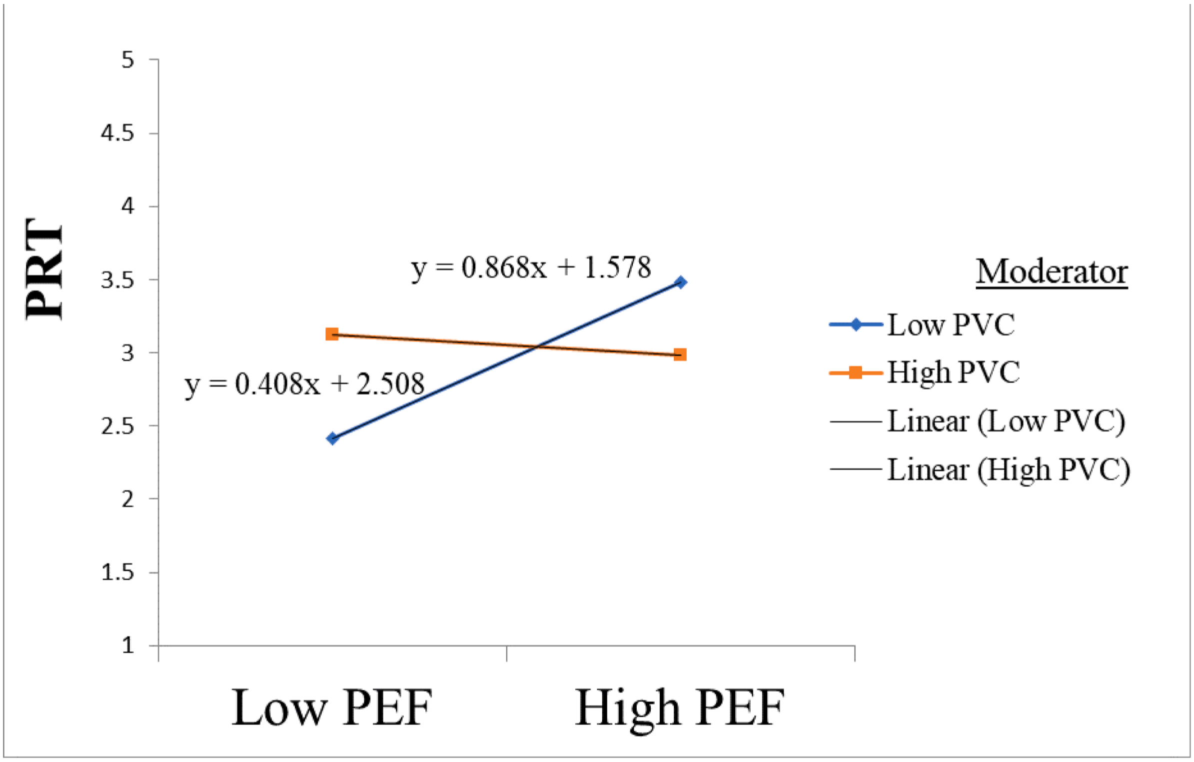

Fig. 3. PVC dampens the positive relationship between PEF and PRT.

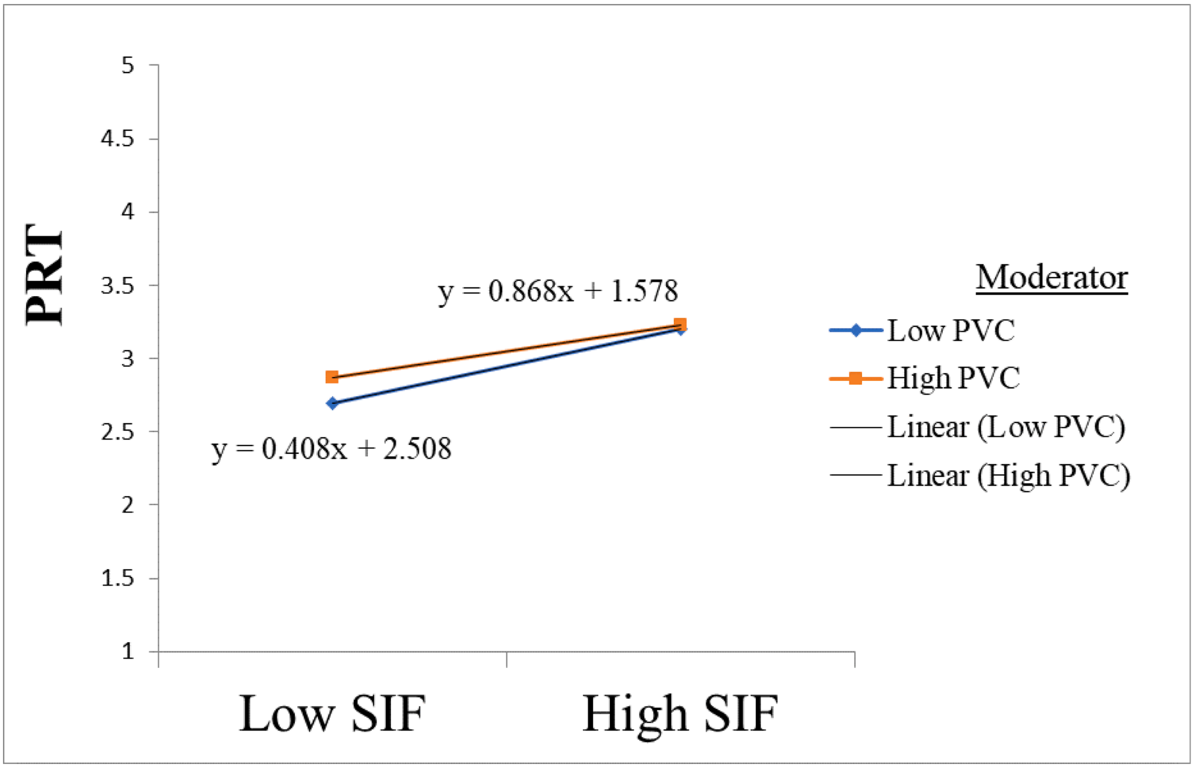

Fig. 4. PVC dampens the positive relationship between SIF and PRT.

The hypothesised relationship between effort expectancy and consumers' trust being weaker with customers with high privacy concerns was not supported. Prior studies have not previously explored this exact relationship. However, the results are not consistent with what was expected. A plausible explanation for this could be that customers are highly concerned about data privacy, and regardless of how easy the system is to use, this concern is still present.

This study's empirical results did not support the proposed hypothesis that the relationship between facilitating conditions and consumers' trust in autonomous shopping is weaker with customers with high privacy concerns. While this exact relationship has not been tested in other studies, it has been found that systems with seal certification and strong privacy compliance rules and procedures make potential users feel at ease (Widjaja et al., 2019). Also, privacy issues have decreased trust and information disclosure (Inman and Nikolova, 2017). Therefore, this finding is inconsistent with the literature's anecdotal evidence. A plausible explanation could be that an autonomous shopping system requires much personal information to function correctly. This disclosure results in privacy concerns for customers. Despite the result showing that facilitating conditions lead to trust formation, privacy concern is still a major issue for customers.

This study has shown that trust positively influences customers' autonomous shopping intention. This result was similar to the findings of Glikson and Woolley (2020) in AI adoption. Cha (2020) also found a positive relationship between perceived trust and intention to use robot-serviced restaurants. This result highlights the importance of building trust toward autonomous shopping systems to increase customers' likelihood of adopting such systems.

4.5. Theoretical implications

The findings of this study provide insights that make the following theoretical implications. First, this study contributes to the popular but still developing research area of customer behaviour and artificial intelligence by being one of the first studies to examine autonomous shopping systems empirically. Researchers have called for more empirical studies in AI (De Bellis and Johar, 2020; Hu et al., 2021). Second, this study answers the call by Tamilmani et al. (2020)'s, recommending the addition of trust as a new variable in the UTAUT model. This study's findings confirm the positive relationship between effort expectancy, performance expectancy, facilitating conditions, and social influence on trust. This result contributes to the UTAUT model and technology adoption research. Third, privacy is added as a moderating variable in the extended UTAUT model. This addition allows for novel relationships to be explored. While studies have modelled privacy concerns directly related to behaviour intention, the moderating impact on the UTAUT variables has not been examined.

4.6. Practical implications

This study's findings are useful for developers of autonomous shopping systems seeking to understand customers' adoption behaviour. By extending the UTAUT model to include trust and privacy concerns, this study examines customers' major concerns, allowing valuable insights to be generated.

Performance expectancy positively influenced customers' trust in autonomous shopping systems. This finding highlights the importance of increasing the benefits associated with the use of this system. Customers need to be aware of how the use of this system would benefit them. This result depicts the important role that needs to be played by marketers in getting this information across to customers. As AI technology and its applications are new, awareness of what it is and its potential benefit is not fully understood. Therefore, developers need to work with marketers to create awareness and make customers realise how autonomous shopping systems can revolutionise the shopping process.

Effort expectancy was also found to influence trust in autonomous shopping systems positively. This signifies the importance of app developers to make autonomous shopping systems easy to use. Such systems should be able to integrate easily with the customer's lifestyle. With the development of the internet-of-things, autonomous shopping systems should be compatible with other customers' devices. This will ensure that customers must put in little effort to make such systems understand their needs and expectations.

Social influence was another factor that positively influenced trust formation toward autonomous shopping systems. This result highlights the importance of reviews, feedback, and recommendations from existing users. Marketers must also be present on social networking sites to facilitate communication with customers and generate positive word of mouth.

Facilitating conditions was another factor that positively influenced customers' trust formation in autonomous shopping systems. This result shows the importance of having support services. Initially, customers may face an issue or have questions and concerns about such systems. They must feel that services such as email support, websites, and live chat are available for customers to resolve their concerns. These support services led to trust perception for customers toward autonomous shopping systems.

This study revealed the significance of privacy concerns regarding autonomous shopping system adoption. Developers and marketers need to reduce this concern to increase the adoption of autonomous shopping systems significantly. Results show that despite customers being motivated to adopt autonomous shopping systems due to several factors, privacy concerns become a major hindrance to adoption. Developers need to work on obtaining privacy seals to assure customers about their privacy concerns. Customers must have full knowledge of what data is collected and how it is used and stored. Such information should be readily available to customers. These practices will increase their ability to trust autonomous shopping systems, ultimately leading to high adoption.

4.7. Conclusion, limitations, and directions for future research

Despite this study incorporating sound research procedures, some limitations need highlighting. First, the generalisation of this study's results is constrained due to the study being conducted in Fiji. Therefore, this study's model can be tested in different countries to generate insights into customers' autonomous shopping adoption intentions in different countries. Second, this study used a sponsored Facebook advertisement to circulate the survey links to respondents. Future studies can attempt to use a random sampling technique to collect data. Third, despite the model of this study having good R^2 values (predictive power), there is room to incorporate other variables to understand better factors driving trust and adoption intention in the context of autonomous shopping systems.

Through adopting a quantitative research design, this study collected data from 454 respondents. The conceptual model of this study extended the UTAUT framework with the addition of trust and privacy constructs. Results show that performance expectancy, effort expectancy, social influence, and facilitating conditions positively impacted perceived trust in autonomous shopping. Privacy concern as a moderator was found to dampen the positive relationship between performance expectancy and perceived trust. Similarly, privacy concerns also dampened the positive relationship between social influence and perceived trust. These findings made noteworthy contributions to customer behaviour and artificial intelligence literature. It also generated practical insights for systems developers and markets to increase the adoption of autonomous shopping systems.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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