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Research paper

Exploring the attitudes and perceptions influencing user participation in gamification schemes for TDM

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ABSTRACT

Travel demand management (TDM) strategies and behaviour change initiatives aim to improve travel conditions by reducing or redistribute demand where the transport system is most congested. TDM strategies with gamified design can provide positive incentives in the form of playing a game and providing rewards. Gamified design has recently been implemented for TDM strategies in the public transport field with some success. However, before implementing a TDM strategy with a gamified design, it is critical to understand how participants or users value the proposed strategy. This study explores which attitudes and perceptions make a gamified scheme successful in attracting users to participate. This study surveyed 160 participants in Taipei City and used structural equation modelling (SEM) with an extended technology acceptance model (extended TAM) to identify which user attitudes and perceptions are critical to influence respondents' intention to join the gamified scheme. This study finds the key element of 'to capture the fun and joy' of the gamified scheme or perceived enjoyment is positively related to perceived ease of use that is key in convincing people to participate as being perceived as easy to use means the target demographic feels no burden in "giving it a try". The results of this study may aid policy makers in designing gamification schemes that are more tailored for the specific purpose and thus more effective.

1. Introduction

Travel demand management (TDM) seeks to reduce travel demand, or to redistribute demand over time or to different locations. In recent years, many innovative TDM instruments have emerged, which use incentives to reduce or shift travel demand from private modes to public transport. Positive user incentives for TDM include policies such as fare discounts, loyalty rewards, and gamification. Fare discounts are often used to manage peak loading by providing cheaper off-peak fares. For example, the public transport system in Brisbane, Australia provides a 20% off-peak fare discount if passengers travel outside a defined peak period. However, peak loading issues still endure and a peak-in-the-peak travel pattern still persists (Yen et al., 2015). Therefore, policy makers or transport planners continue to seek more effective TDM strategies to address issues such as peak loading. Gamification has been gaining traction as an innovative non-traditional TDM policy. Gamification refers to the introduction of game design elements into non-game contexts (Deterding et al., 2011:1).

The success of gamification schemes for TDM has only recently started to be explored. In public transport, previous research has shown that gamification is effective at reducing travel demand in peak hours, such as Singapore's INSINC program which successfully shifted 7.49% of peak demand to the off-peak period in a six-month research pilot in 2012 (Pluntke & Prabhakar, 2013). INSINC was a fully designed scheme that was implemented with success with no pre-scheme investigation. However, Yen et al. (2019) argued that, for every gamification scheme, there should be pre-scheme investigation to understand what elements or design factors can catch the attention of target users. For understanding behaviour intention, the attitudes and perceptions of potential target users are two key aspects to investigate (Eccarius & Lu, 2020; Lai et al., 2015; Liang et al., 2019; Zailani et al., 2016). Thus the main research question for this study is: which attitudes and perceptions toward a gamification scheme in public transport can significantly motivate the target user(s) to join and participate in the scheme?

To understand the effectiveness of gamification schemes at capturing potential users, this study uses a modified Technology Acceptance Model (TAM) to analyze the perceptions of potential users of gamified schemes with the aim of reducing public transport peak hour travel. The TAM captures users' perceptions of, or attitudes to, new technologies with four measurements: perceived usefulness, perceived ease of use,

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attitude and behavioural intention (Davis, 1989). However, other authors have used similar measurements, such as social norm (Dickinger et al., 2008) and cohesion (Bollen & Hoyle, 1990). This study proposes a modified TAM, called an extended TAM, with eight measures: perceived security, social norm, perceived cohesion, perceived enjoyment, perceived usefulness, perceived ease of use, attitude towards playing, and behavioural intention. A questionnaire survey was used to collect data in 2021 in Taiwan. Participants were asked about their attitudes and perceptions to proposed schemes as well as their intention to participate. The analysis in this study uses structural equation modeling (SEM) for the extended TAM.

The paper is organised as follows. Section 2 reviews the literature of how gamification can be implemented in the transport field and presents an example of SEM and TAM in the field of gamification. Section 3 describes the methodology used to conduct the study, including the questionnaire survey design, and the SEM using the bias-corrected factor score path analysis method (Kelcey et al., 2018). Section 4 provides basic statistical analysis of the collected data. Analysis results of the SEM model are presented in Section 5, and the results and their implications are discussed in Section 6. The final section provides a conclusion and recommendations for further research in this area.

2. Literature review

2.1. Gamification in transport

2.1.1. Travel demand management (TDM)

Travel demand management (TDM) schemes often include various incentives to encourage users to change their behaviour (Yen et al., 2019) with the aim of promoting more sustainable transport. In the early days, TDM was mainly used to attempt to decrease the demand for private vehicle use with view to reducing the negative environmental impacts, such as congestion, noise, and air pollution (Gärling & Schuitema, 2007; Garling & Schuitema, 2007; Kitamura et al., 1997). Given the effectiveness of TDM in vehicle management, TDM has been implemented more widely to address different travel behaviour, such as parking management (e.g., Petiot, 2004), traffic congestion relief (e.g., Logan et al., 2020), driving safety (e.g., Yen et al., 2022), public transport management (Yen et al., 2015, 2018). In particular for public transport management, off-peak hour fare discounts have been one of the most frequent TDM strategies to attempt to shift peak to off-peak travel. In Brisbane, Australia as an example, if a user travels with a public transport smart card during off-peak periods (i.e., 8.30am-3.30pm and 7pm-6am the next day), their fare will have a 20% discount. However, Yen et al. (2016) have reported an obvious peak in the peak travel pattern that still can be observed, even with this off-peak discount. This has led policy makers and scholars to start looking for a more effective TDM strategy and gamifcation is one of the design concepts that has been introduced in recent years. The INSINC program is a TDM scheme which includes gamification in Singapore that has been viewed as one of the more successful schemes in achieving peak spreading and mode shifting from private to public transport. However, this peak demand problem exists for most public transport systems (and urban road systems giving rise to congestion) since many individuals attempt to travel at a similar time (e.g., peak hours): this leads to capacity limitations, not to mention a series of negative externality that might be caused (e.g., delays, crowding, unreliability). Therefore, this study aims to achieve peak spreading via gamified TDM due to its serious impacts on the public transport system.

2.1.2. Gamification

Applying gamification elements to a transport related scheme requires policy makers to consider the nature of transport as a derived demand. Thus the game itself should only be considered as the means to an end, and not the end product. In the context of transport and its derived demand characteristics, gamification can be applied either to the derived demand itself (i.e., travel) or the product or activity (e.g., being at work or school) as the final good or service (Yen et al., 2019). In general, gamification is applied to three main types of TDM strategies: reducing peak congestion, encouraging public transport use, and encouraging safe driving behaviour. Previous studies have shown that gamified TDM schemes are usually paired with varying types and amounts of reward prizes. This study collected and reviewed various literature worldwide on gamification in transport, such as public transport, young driver safety, and active transport. Table 1 summarizes the literature on gamification by geographic location. In terms of results, many of the studies only considered basic statistics with some statistical analysis (please refer to Table 1 for more details). Some schemes had self-reported results (e.g., S-Drive[1] application in Sydney, Australia) to indicate the effects of the proposed scheme without revealing the underlying analysis, data or related details. A smaller number of gamification related studies used predictive statistical models, where the most commonly used statistical models were SEM and choice modelling. The use of gamification in the public transport field is relatively new and understanding the role of users' perceptions in participating in a scheme means finding an approach to analysis which allows the role of these factors which cannot be directly observed from the actual or intended behaviour. SEM is appropriate for analysis given its ability to model underlying factors to the outcome variable,

Previous studies have focused on several fields of transport in applying gamified design for TDM. Transport safety has the most applications of gamification. In transport safety, rewards and gamified discounts may be used to encourage young drivers to practice safer driving behaviour (Ambrey & Yen, 2018; Yen et al., 2019, 2022). However, research in this field is lacking, and most of the schemes self-report the scheme effects (e.g., S-Drive). In active transport, gamification is usually applied in the form of leader boards, or games that encourage younger people, such as primary school students, to be more active with dual purposes of improving health and reducing traffic congestion (Coombes & Jones, 2016; Weber et al., 2018). Applications in public transport include two main types: encouraging public transport use and avoiding the peak. Modal shift schemes aim to encourage private car users to shift to public transport. Peak avoidance schemes aim to relieve peak hour congestion in the public transport network (Pluntke & Prabhakar, 2013; Yen et al., 2019). Peak avoidance schemes may also be applied to road traffic management to reduce congestion during peak periods (Ben-Elia & Ettema, 2011; Knockaert et al., 2012).

In terms of the effectiveness of gamification schemes, the literature confirms that participants actually change their behaviour or, in other words, the type of experiment affects its measured effectiveness. Generally, in revealed preference experiments (i.e., actual trials), a smaller percentage of participants show a change of behaviour than in stated preference experiments (e.g., survey experiments) where participants only express whether they would be willing to change their behaviour or not. For revealed preference experiments in public transport, the behaviour change ranges from 5% to 47% (Bowden & Hellen, 2019; Castellanos, 2016; Wall et al., 2017). In active transport, the percentage change is between 4% and 26% (Coombes & Jones, 2016; Kazhamiakin et al., 2015; Tsirimpa et al., 2019). For stated preference experiments, the behaviour change rate is much higher in general, with more than 50% of participants stating that they are willing to change their behaviour (Koo et al., 2013; Mehdizadeh Dastjerdi et al., 2019; Rey et al., 2016).

In many previous studies for both RP and SP experiments, schemes are pre-determined with all scheme parameters pre-set, such as reward types and reward amount. The question for these studies was then how would participants react to pre-determined schemes. However, to design

[1] https://www.campaignasia.com/agencyportfolio/CaseStudyCampaign/387864,case-study-how-samsung-tackled-safe-driving-with-an-app.aspx#.YcPuX2hBxD8.

Table 1
Review of gamification in transport applications, by location.

Authors	Geographic location	Scheme Type	Analysis Method	Data Collection Method	Rate of Success**
Multiple Locations					
Wunsch et al. (2016)	Austria, United States	RP experiment with leader boards and monetary rewards, focus on increasing active transport use	Basic statistics,Chi-square test	Real game APP data	26% of participants
Weber et al. (2018)	Australia, United Kingdom, United States	RP experiment with leader boards, focus on increasing active transport use	Basic statistics	Real game APP data	4–12.8% of participants
Europe					
Bamberg et al. (2003)	Germany	RP experiment with lottery rewards, focusing on mode switching to public transit	SEM	In-person survey	16.5% of participants
Ben-Elia and Ettema (2011)	The Netherlands	RP experiment with monetary and free goods rewards, focusing on peak avoidance and mode switch	Choice model	Real game data	25% of participants
Knockaert et al. (2012)	The Netherlands	RP experiment with monetary and free goods rewards, focusing on driver peak avoidance	Choice model	Real game data	25–30% of participants
Khademi et al. (2014)	The Netherlands	RP experiment with monetary and free goods rewards, focusing on peak avoidance and mode switch	Choice model	In-person survey	40% of participants
Kazhamiakin et al. (2015)	Italy	RP experiment with leader boards, focusing on mode switch to active transport	Basic statistics	Real game data	18% of participants
Coombes and Jones (2016)	United Kingdom	RP experiment with leader boards, focusing on mode switch to active transport	Multiple regression	Real game data	10% of participants
Peer et al. (2016)	The Netherlands	RP experiment with monetary and free goods rewards, focusing on peak avoidance and mode switch	Choice model	Real game data	19% of participants
Wall et al. (2017)	United Kingdom	RP experiment with discounts as incentives, focusing on mode switch to public transit	Basic statistics	Online survey	22% of participants
Bowden and Hellen (2019)	Italy	RP experiment with gifts and discounts as incentives, focusing on mode switching to public transit	Basic statistics	Real game APP information	47% of participants
Drakoulis et al. (2018)	Greece	RP experiment with gifts and leader boards, focusing on mode switching to demand responsive transport service	Basic statistics	Real game APP information	20% of participants
Lieberoth et al. (2018)	Denmark	RP experiment with lottery rewards, focusing on mode switching to public transit	Basic statistics	Official data from local government	4% of participants
Polydoropoulou et al. (2018)	Austria, Slovenia, United Kingdom	SP survey experiment using both cash and non-monetary gifts as incentives, and focusing on reducing car use by switching to other modes	Choice model	Online survey	17% of participants
Mehdizadeh Dastjerdi et al. (2019)	Denmark	SP survey experiment using both monetary and non-monetary incentives and focusing on incentivizing green multimodal travel	SEM	Online survey	70% of participants
Tsirimpa et al. (2019)	Austria, United Kingdom	SP and RP experiments using different types of gamified and non-gamified incentives and focusing on incentivizing multimodal travel	Choice model (SP + RP), Basic statistics (RP)	Online survey, Real game APP information	17–20% of participants (RP), 79% of participants (SP)
Asia and Australia					
Koo et al. (2013)	South Korea	SP survey experiment using gifts and discounts as incentives, and focusing on mode switch to public transit	Choice model	In-person survey	93% of participants
Pluntke and Prabhakar (2013)	Singapore	RP experiment using lottery style monetary and non-monetary incentives, focusing on peak avoidance for public transit users	Descriptive statistics	Real game experiment data	7–10% of participants
Zhang et al. (2014)	China	SP survey experiment, using discounts and monetary rewards as incentives, focusing on peak avoidance for public transit users	Binomial logistic regression	Online survey	96% of participants
Chidambaram et al. (2014)	India	SP survey experiment, using discounts and monetary rewards as incentives, focusing on mode switch into public transit	Choice model	In-person survey	4–9% of participants
Rey et al. (2016)	Australia	SP survey experiment using lottery rewards, focusing on peak avoidance for public transit users	Choice model	In-person survey	65% of participants
Voon et al. (2016)	Brunei	SP and RP experiments using gifts and discounts as incentives focusing on mode switch to public transit	Descriptive statistics	Online survey, Real game APP data	35% of participants
Ambrey and Yen (2018)	Australia	SP survey experiment with discounts and gamified rewards as incentives and focusing on encouraging safe driving behaviour	Choice model	Online survey	33% of participants
The Americas					
Leblanc and Walker (2013)	United States	SP survey experiment with different types of TDM schemes including gamified rewards, focusing on mode switch to public transit or active transport or peak avoidance for car users	Choice model	In-person survey	40–47% of participants
Castellanos (2016)	Colombia	RP experiment using cash as an incentive and focusing on mode switch to public transit or active transport	Basic statistics, Chi-square test	Real game APP information	9% of participants

gamification schemes that are more effective in changing behaviour it is important to understand potential participants' attitudes and perceptions.

2.2. Behaviour theory

2.2.1. Perceptions and attitudes

Behaviour theory studies how individuals act. In the case of gamification, the schemes are usually applied with some type of technology, for example, mobile phone applications (e.g., Castellanos, 2016; Kazhamiakin et al., 2015). There are several factors behind a person's decision to adopt a new technology (or gamified scheme in this case). With transport services increasingly using digital technologies, the TAM (Davis, 1989) can be a useful model to measure the effects and efficacy of new technology. The TAM has two primary factors influencing an individual's intention to use a new technology: perceived usefulness and perceived ease of use, as shown in Fig. 1. For example, an older adult who perceives digital technologies as too difficult to play or a waste of time (e.g., low perceived ease of use) would be unlikely to adopt these technologies (i.e., no actual use). In contrast, an older adult who perceives digital technologies as providing value to their life and as easy to learn (e.g., high perceived ease of use) will be more likely to learn how to adopt these technologies (i.e., actual use).

In the TAM model, perceived usefulness and perceived ease of use are affected by different external variables (e.g., experience, familiarity with the technology), and, at the same time, perceived usefulness and perceived ease of use affect a person's attitude to adopt a particular technology. This attitude in turn affects the person's behavioural intention, which determines whether the person will be willing to use a certain piece of technology or not. Moon and Kim (2001) stated that to increase external validity of the TAM, it is necessary to further explore the nature and specific influences of technological and usage–context factors (e.g., perceived cohesion) that may alter the user's acceptance. Usage–context factors refer to how personal background (e.g., peers) and/or social surroundings (e.g., colleagues) might influence an individual's attitude or intention of adopting a technology or changing their behaviour. In the context of web applications, perceived usefulness has been proven that it might not have an absolute positive effect on behavioural intention (Liu & Li, 2011; Mallat et al., 2009). Mallat et al. (2009) stated that context or situation is a variable that can positively mediate the effect of perceived usefulness on behavioural intention in the use of mobile web applications. Since this study aims to understand the adoption of a gamification scheme that uses a mobile phone application, perceived usefulness and perceived ease of use experience a similar phenomenon relating to their direct positive effect on behavioural intention.

Gamification schemes in transport are often delivered through mobile or web applications (Castellanos, 2016; Kazhamiakin et al., 2015; Mehdizadeh Dastjerdi et al., 2019), especially in recent years as smartphone technology is becoming increasingly more common. In the past user behaviour for travel demand schemes has usually been analysed using the Theory of Planned Behaviour (TPB) which proposes that an individual's behaviour is based on behavioural intention, shaped by different perceptions (Ajzen, 1991). Behavioural intentions are influenced by the attitudes toward the behaviour, subjective norm, and perceived behavioural control (i.e. perceptions). Fig. 2 presents the model structure of the TPB. Elements of the TPB can be combined into the TAM to create a more complete model, including perceived ease of use and perceived usefulness, and at the same time measuring perceptions such as subjective norm. Taylor and Todd (1995) expressed that combining elements of the TAM and TPB is useful to define an individual's behaviour in using new technology.

There are some more perceptions and attitude aspects are considered in literature. Perceived ease of use refers to the extent to which an individual believes that using a particular system is free of effort (Davis, 1989). Perceived usefulness refers to the extent to which an individual believes that using a particular system would improve the performance (Davis, 1989). Attitudes toward the behaviour refer to an individual's favourable or unfavourable response to a particular behaviour (Ajzen & Fishbein, 2005). Behavioural intentions refer to the belief that an individual will in fact perform a certain behaviour (Ajzen & Fishbein, 2005). Social norm (also known as subjective norm) refers to an individual's reaction to social preferences on performing a particular behaviour (Dickinger et al., 2008). Perceived cohesion refers to the extent to which individual group members feel "stuck to", or a part of, particular social groups (e.g., workers) (Bollen & Hoyle, 1990). Perceived enjoyment refers to the extent to which an activity is perceived to be enjoyable in its own right (Davis, 1989). Perceived security encompasses three dimensions: reliability, safety and privacy (Nui Polatoglu & Ekin, 2001). For this research, perceived security is defined as the extent to which an individual believes that using a piece of technology satisfies these three dimensions.

2.2.2. Structural equation modelling

SEM is a statistical technique that can be used to explain the complex relationships among multiple variables. This technique was first developed as path analysis, without the use of latent variables (Wright, 1921). SEM usually deals with latent variables or constructs, which are variables that are unobservable and cannot be directly measured. The latent variables are represented by multiple measured variables. During this process, the relationships previously mentioned are expressed as a series of equations, in the likelihood of a series of multiple regressions. This process is also known as confirmatory factor analysis (CFA) (Jöreskog, 1969). This relationship is demonstrated graphically in Fig. 3. Each latent variable ε_n is explained by a number of observable variables x_n; the coefficient estimates λ_{mn} represent how much each observable variable explains the latent variable. There is also an error term δ_n for each observable variable. Correlation between latent variables is also possible, and is represented by φ_{mn}.

SEM is a term used to specify, estimate, and evaluate models of linear models among a set of observed variables in terms of an often smaller number of unobserved variables. SEM has been used to analyze gamification schemes in both transport (Mehdizadeh Dastjerdi et al., 2019) and other areas such as education (Su & Cheng, 2013) and healthcare (Lee et al., 2017), among others. The study uses SEM to estimate the eight unobserved latent variables in the extended TAM structure, and to subsequently estimate the linear regression relationships between the latent variables. As a result, for the exploratory research in this study, SEM is an appropriate method to explore the perceptions and attitudes of users for public transport gamification schemes.

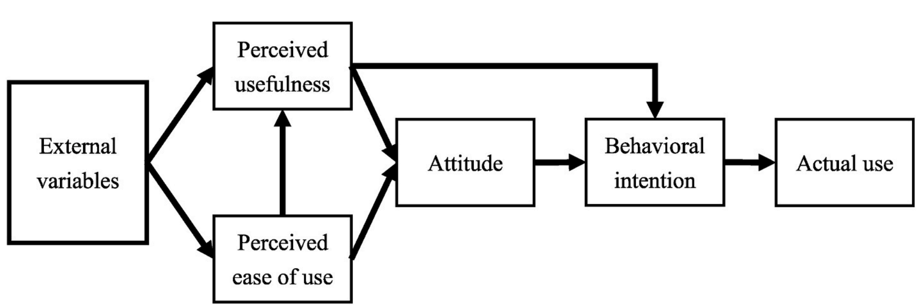


Fig. 1. Technology acceptance model (Davis, 1989).

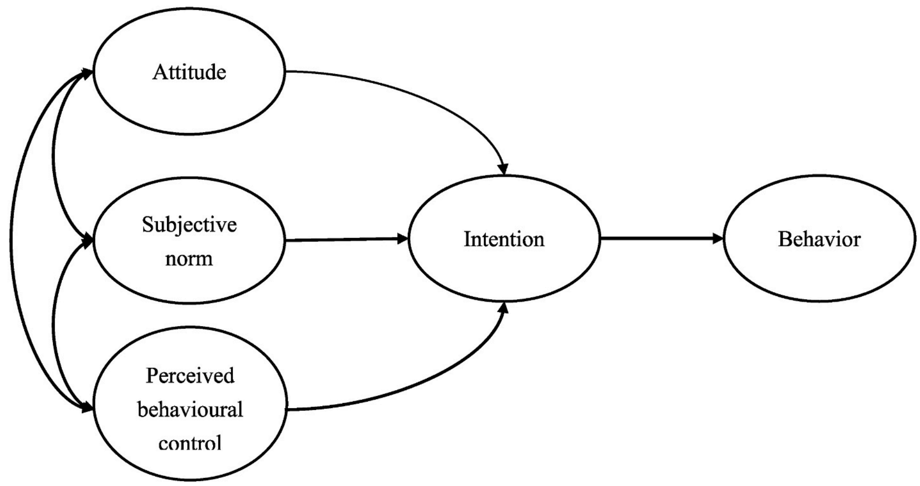


Fig. 2. Theory of planned behaviour (TPB) (Ajzen, 1991).

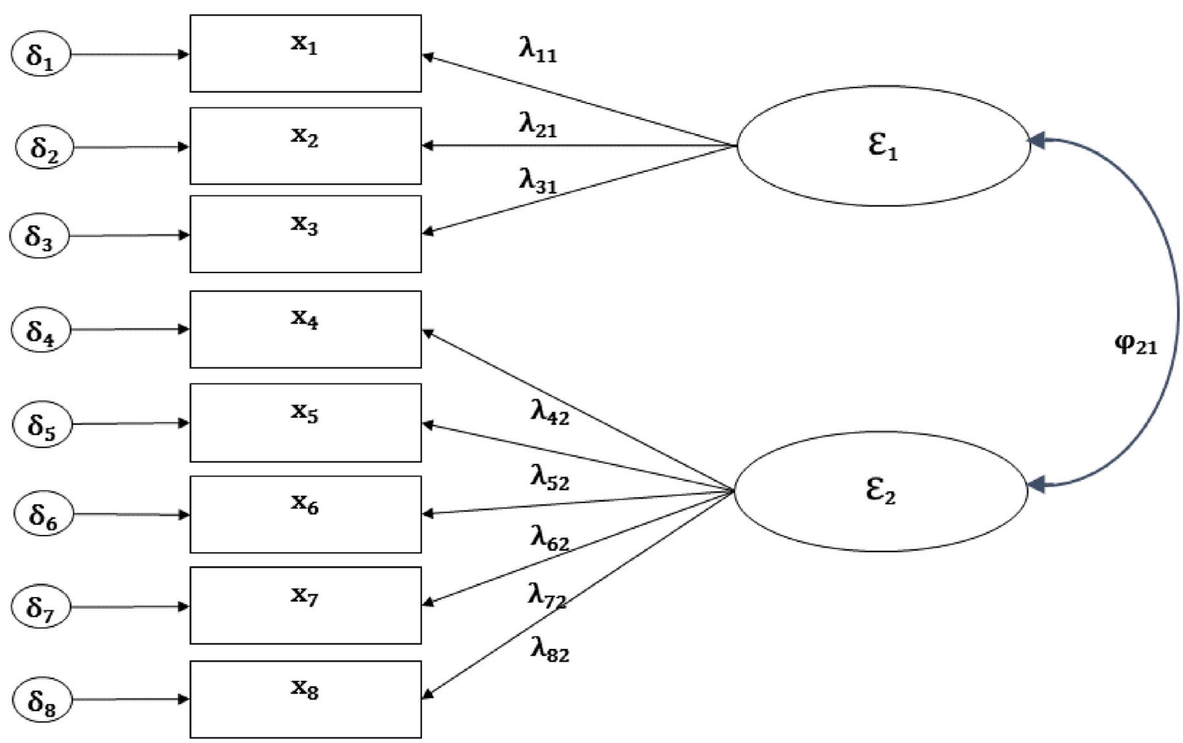


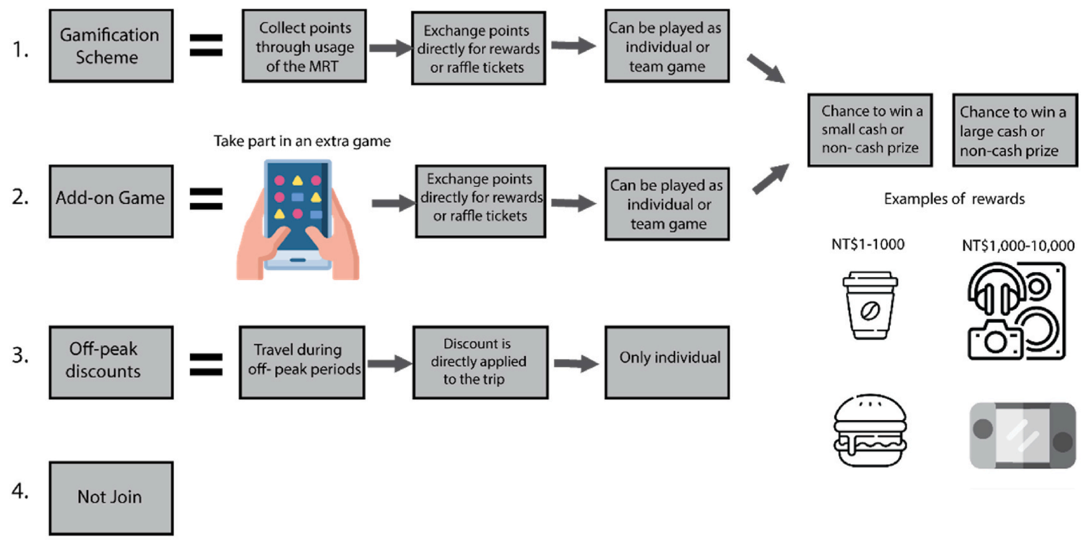
Fig. 3. Example of a SEM model structure (Jöreskog & Sörbom, 1996).

3. Methodology

3.1. Study design

This study created a hypothetical gamified scheme applied to the Taipei City public transport network to present to survey respondents. The designed gamified schemes were adopted from a previously designed scheme by Ambrey and Yen (2018). In total, there are four schemes or choices: two gamified schemes (i.e., a gamification scheme and an Add-on game scheme), one incentive scheme (i.e., off-peak discount scheme) and 'not join' scheme. The schemes are described in Fig. 4. After reading the description of the four schemes, respondents were asked to select their preferences for 24 measurement items from the extended TAM constructs (as shown in Fig. 5). These items or questions measure the respondents' attitudes to and perceptions of each scheme and are used in the SEM modelling. Each of the eight constructs in the SEM model has three measurement items, yielding 24 measurement items, measured on a 6-point Likert scale, with 1 = 'strongly disagree', 2 = 'disagree', 3 = 'slightly disagree', 4 = 'slightly agree', 5 = 'agree' and 6 = 'strongly agree'. Sociodemographic information from the respondents was also collected for further analysis.

The target respondents of the survey were people who are living or commuting in Taipei City or New Taipei City. The main criteria was that the respondent makes at least one weekly trip with an origin or destination in Taipei City or New Taipei City by any mode. The survey was distributed online through social media channels. The survey was deemed complete when 160 valid responses were successfully collected due to funding limitations. The data was collected from January to March 2021.



Point collection and rewards exchange
1. For every off-peak ride, the player obtains 20 points.
2. For using the public transport system, the player obtains 5 points.
3. When the player collects 500 points, these can be exchanged for a reward or for a raffle ticket. Points are calculated monthly.

Fig. 4. Information provided to respondents for the designed gamification scheme.

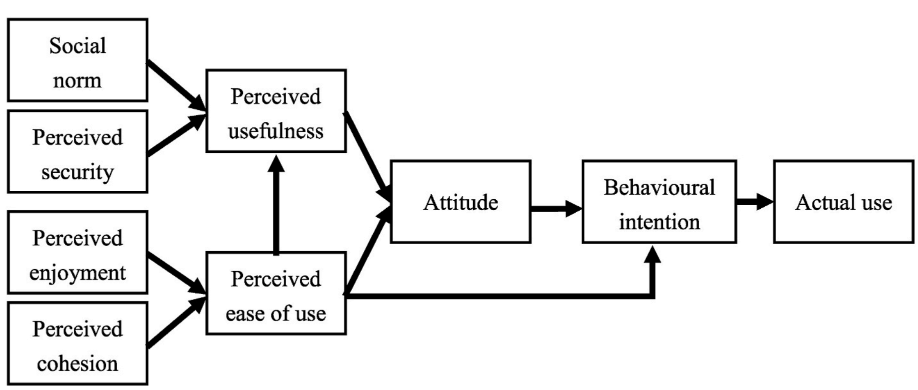


Fig. 5. The extended TAM

3.2. SEM model structure

Based on the literature, this study proposes an extended TAM model, where four more factors (i.e., social norm, perceived cohesion, perceived enjoyment and perceived security) are added to the TAM of perceived usefulness and ease of use. The proposed structure, or relationship between constructs, is shown in Fig. 5. Each factor in the extended TAM is defined as follows in this study. This study proposes the extended TAM model combines elements of TPB (e.g. social norm) into the TAM to create a more complete behaviour model. The proposed structure for the extended TAM to be used in the SEM is presented in Fig. 5.

The SEM model has eight latent variables (i.e., constructs), measured by three measurement items each. The eight latent variables and the respective measurement items from the questionnaire survey are summarized in Table 2. Question statements were validated by being taken from previous TAM surveys (e.g., Ambrey & Yen, 2018; Choi & Kim, 2004; Davis, 1989; Hsu & Lu, 2004, 2007; Venkatesh, 2000; Yen et al., 2022).

The extended TAM model proposed by this study contains four extra constructs as compared to the traditional TAM model, including social norm, perceived cohesion, perceived enjoyment, and perceived security. The formulated SEM model is shown in Fig. 6. The following hypotheses are tested in this analysis:

H1. Social norm has a positive direct effect on perceived usefulness (Venkatesh, 2000).

H2. Social norm has a positive direct effect on perceived security (Ho et al., 2017).

Table 2
Summary of latent and measurement items.

Latent Variables	Variable Code	Measurement Items
Social norm (SN)	x_{11}	I want to participate in this scheme because my classmate(s) is/are participating
	x_{12}	I want to participate in this scheme because my colleague(s) is/are participating
	x_{13}	I want to participate in this scheme because my friend(s) is/are participating
Perceived ease of use (PE)	x_{21}	Learning to participate in this scheme will be easy for me
	x_{22}	It will be easy to participate in this scheme
	x_{23}	It will be easy for me to be skilful in this scheme
Perceived cohesion (PC)	x_{31}	I believe I will fit in well with the scheme
	x_{32}	I believe I will like the other participants in this scheme
	x_{33}	In general, I believe the participants in this scheme will act as a union
Perceived enjoyment (EN)	x_{41}	Participating in this scheme will be enjoyable
	x_{42}	Participating in this scheme will be thrilling
	x_{43}	Overall, participating in this scheme will be entertaining
Perceived usefulness (PU)	x_{51}	I believe this scheme applies to me
	x_{52}	I believe I should participate in this scheme
	x_{53}	I believe I have nothing to gain from this scheme[a]
Attitude toward playing (AT)	x_{61}	I will like participating in this scheme
	x_{62}	I feel good about participating in this scheme
	x_{63}	In general, I will have positive feelings towards this scheme
Behavioural intention (BI)	x_{71}	It will be worth playing in such schemes
	x_{72}	I will actively be involved in such schemes in the future
	x_{73}	I have intentions to participate in this scheme again
Perceived security (PS)	x_{81}	I am confident that the private information I provide with the scheme will be secure
	x_{82}	While participating in this scheme, I believe that the security system will confirm my identity before disclosing account information
	x_{83}	While participating in this scheme, I believe that the security system does not allow unauthorized access to the account

[a] This item is a negative statement, and it was reverse coded to match the rest of the data.

H3. Social norm has a positive direct effect on perceived cohesion (Bollen & Hoyle, 1990).

H4. Perceived security has a positive direct effect on perceived usefulness (Lallmahamood, 1970).

H5. Perceived security has a positive direct effect on perceived enjoyment (Hwang & Kim, 2007).

H6. Perceived cohesion has a positive direct effect on perceived ease of use (Bollen & Hoyle, 1990).

H7. Perceived enjoyment has a positive direct effect on perceived ease of use (Venkatesh, 2000).

H8. Perceived usefulness has a positive direct effect on attitude towards playing (Davis, 1989).

H9. Perceived ease of use has a positive direct effect on perceived usefulness (Davis, 1989).

H10. Perceived ease of use has a positive direct effect on attitude towards playing (Davis, 1989).

H11. Perceived ease of use has a positive direct effect on behavioural intention (Liu & Li, 2011; Mallat et al., 2009).

H12. Attitude towards playing has a positive direct effect on behavioural intention (Davis, 1989).

The relationship of the traditional TAM structure has been tested by various studies (e.g., Beldad & Hegner, 2018; Chang et al., 2019; Lallmahamood, 1970). Some studies considered extra latent variables. However, most previous studies only focused on one latent variable. Taking social norm as an example, social norm has been used in previous studies in combination with the TAM to research how it affects behavioural intention in gamified mobile apps (Beldad & Hegner, 2018). In this case study in Taiwan, potential latent variables, including social norm, perceived security, perceived cohesion and perceived enjoyment, are all included to investigate the relationships among them. Based on previous studies, social norm, perceived security, perceived cohesion and perceived enjoyment are set to have indirect effects on attitude towards participating, and therefore on behavioural intention. The effects are mediated by both perceived usefulness and perceived ease of use (Beldad & Hegner, 2018; Chang et al., 2019; Lallmahamood, 1970). Fig. 6 shows the SEM structure for the extended TAM with 24 measurement items.

Although this study has a sample size of 160, it is classified as a small sample size due to the complexity of the SEM model structure. Consequently, the SEM model is estimated through a bias-corrected factor score path analysis method (BCFSPA) (Kelcey, 2019). This estimation method separates the model into smaller parts to allow for better estimation and accounts for bias from covariance caused by small sample size, giving a consistent and robust estimate for complex models, even with sample size as low as 100. Previous research has compared the robustness and performance of BCFSPA relative to full information methods in small sample sizes and with a regular SEM model set up, including moderate model complexity (Lu et al., 2011), non-normal indicators in simple regression (Devlieger et al., 2016), measurement model misspecifications (Devlieger & Rosseel, 2017), and multilevel or clustered settings (Kelcey et al., 2018). All these studies confirm and conclude the BCFSPA method can provide less biased results for a complex SEM structure.

The estimation process is carried out in four steps, as previously set out by Kelcey (2019):

- Step 1: Confirmatory factor analysis models were separately estimated for each latent variable. Eight factor models were estimated in total. After assessing each model, goodness for each latent factor was then estimated using Chi-square tests.
- Step 2: Factor scores for each latent variable are separately predicted, without allowing for correlation. This is done using the regression method. Subsequently, these factor scores are used to estimate the variance-covariance matrix for the factor scores. The scores calculated in this step are not the final factor scores, and they are only used to obtain the variance-covariance matrix estimate.
- Step 3: The covariance matrix is corrected in order to obtain the true covariance of the model. The covariance is divided between each set of factor scores by the respective product of the factor scores and the loading matrices. Conceptually, these corrections parallel the classical test theory disattenuation corrections for a correlation between two unreliably measured constructs because the BCFSPA corrections principally leverage the unreliabilities of the latent variables to remove the attenuating effects of measurement error on the covariances of factor scores (Spearman, 1904). Using the BCFSPA approach allows us to map out the relationships between factor covariances and factor score covariances in order to develop corrections based on these relationships.
- Step 4: After obtaining an unbiased estimate of the true covariance matrix, a typical path analysis is conducted to obtain the unbiased structural path coefficients.

4. Basic statistics

This section presents the descriptive statistics of the survey, as well as

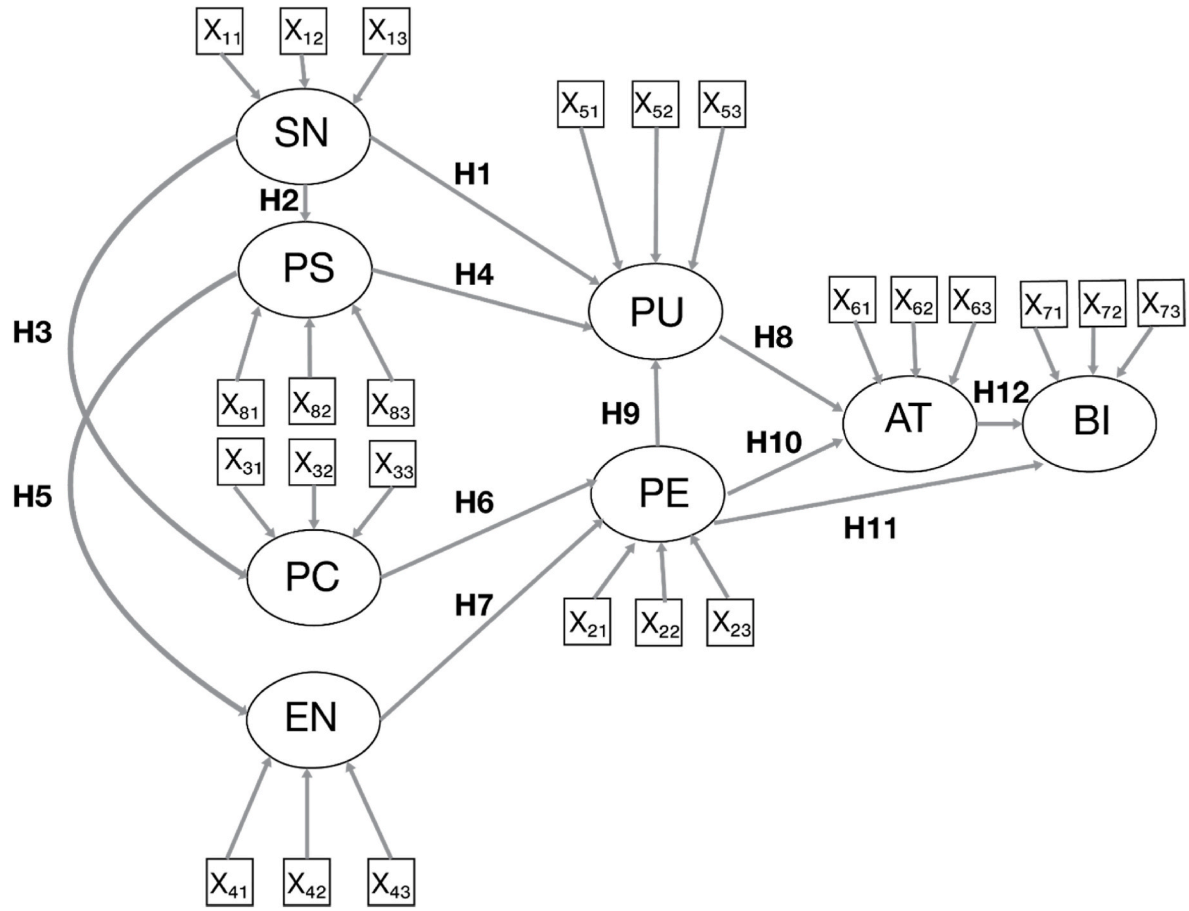


Fig. 6. SEM diagram for extended TAM with 24 measurement items.

the reliability measurements of the SEM constructs.

4.1. Descriptive statistics

Table 3 contains the descriptive statistics for the sample. Respondents are almost evenly split between male (47%) and female (53%). The majority of respondents (around 80%) are younger than 35, and the average age of the sample is 31 years old. Over half of respondents (54%) had a full-time job, and almost all respondents have received higher education (e.g., university or vocational school education).

Table 3
Descriptive statistics of the survey.

Variable		Percentage	Variable		Percentage
Sociodemographic variables			Trip characteristics		
Gender	Male	47	Trip purpose	Work: 47%	47
	Female	53		Study: 27%	27
Age	24 or younger	37		Leisure: 26%	26
	25 to 34	41	Main mode used	MRT: 43%	43
	35 to 44	10		Bus: 23%	23
	45 to 54	4		Car: 6%	6
	55 to 64	2		Motorbike: 18%	18
	65 or older	6		Active transport: 5%	5
Occupation	Student	35		Other: 5%	5
	Full time job	54	Average trip frequency		4 times a week
	Other	11			
Education	University or higher	96			
	Master degree or higher	48			

*Return trips.

Regarding the respondents' trip characteristics, 47% stated that their main trip purpose for their most common trip was to go to work, and 27% stated their main trip purpose was to study. This means a total of 74% of respondents can be considered daily commuters. On average, respondents made around 4 return trips a week. In terms of transport mode choice, 72% of trips were on public transport, with a majority of these on MRT (43%), and 28% of trips were by private vehicle, with a majority of these by riding a motorbike (18%). Taiwan has very high motorbike use and relatively low private car mode share (6%). This m pei City.

4.2. Reliability testing

Before conducting the SEM analysis, the data was tested for reliability to ensure that the model can accurately represent the participants' perspectives. The internal consistency of the measurement items was measured via Cronbach's Alpha statistic for the latent variables. The reliability measures were of an acceptable level and well above the cut-off of 0.7. Composite reliability (Fornell & Larcker, 1981) was also estimated for this same purpose. Netemeyer et al. (2003) suggest a measure of composite reliability of 0.8 or more for a narrowly defined construct. In this study, all latent variables have a reliability measure above 0.8, and thus can be considered internally consistent. The basic statistics for the eight constructs are shown in Table 4.

Table 4
Latent variable descriptive statistics and reliability test results.

Latent Variable	Number of Items[a]	Mean	Standard Deviations	Cronbach's Alpha statistic	Composite Reliability
Social norm (SN)	3	3.18	1.51	0.935	0.935
Perceived ease of use (PE)	3	4.15	1.30	0.905	0.897
Perceived cohesion (PC)	3	3.44	1.45	0.831	0.833
Perceived enjoyment (EN)	3	4.06	1.29	0.926	0.927
Perceived usefulness (PU)	3	3.91	1.40	0.883	0.879
Attitude toward playing (AT)	3	4.16	1.29	0.906	0.903
Behavioural intention (BI)	3	4.09	1.27	0.927	0.927
Perceived security (PS)	3	3.56	1.38	0.881	0.887

[a] Measurement i tems are measured on a 6-point Likert scale, ranging from 1 = "strongly disagree" to 6 = "strongly agree".

5. Model results

This results section addresses the main research question of this study of which attitudes and perceptions toward the gamified scheme significantly influence target users in choosing to participate in the scheme.

The final model result is presented in Fig. 7. The BCFSPA method has the disadvantage of lacking reliable fit measurements. Devlieger et al. (2019) state that conventional fit indices (e.g., CFI, RMSEA) used in full information estimated SEM models are not suitable for model fits calculated at low sample sizes. Instead, a Chi-square is used to measure the reliability of the model (Suhr, 2008). For the final model, the Chi-square test statistic is 1.326 with a p-value under 0.05; thus, the model has an acceptable goodness of fit. Table 5 shows goodness of fit statistics.

In line with previous studies, model results of this study also confirmed that perceived ease of use is significantly and directly related to behavioural intention (Mallat et al., 2009). This means that, the easier the proposed scheme is to use, the higher the intention to use it will be and this would result in higher participation. Three more correlations were found between the extended constructs (i.e., social norm, perceived security, perceived cohesion and perceived enjoyment). Social norm affects perceived cohesion and perceived security. Perceived security has a moderating effect on the relation between social norm and perceived usefulness. Social norm is also correlated with perceived cohesion. Perceived security is correlated with enjoyment.

Fig. 7 presents the model results and these are consolidated in terms of measurement model fit, direct effects and indirect effects. All of the estimates are statistically significant at the 0.01 level. These estimates represent the standardized effect that each measurement item value has

Table 5
Goodness of fit statistics.

Chi squared	Degrees of freedom	χ2/df	Ideal Value
397.86	300	1.326	<3.00

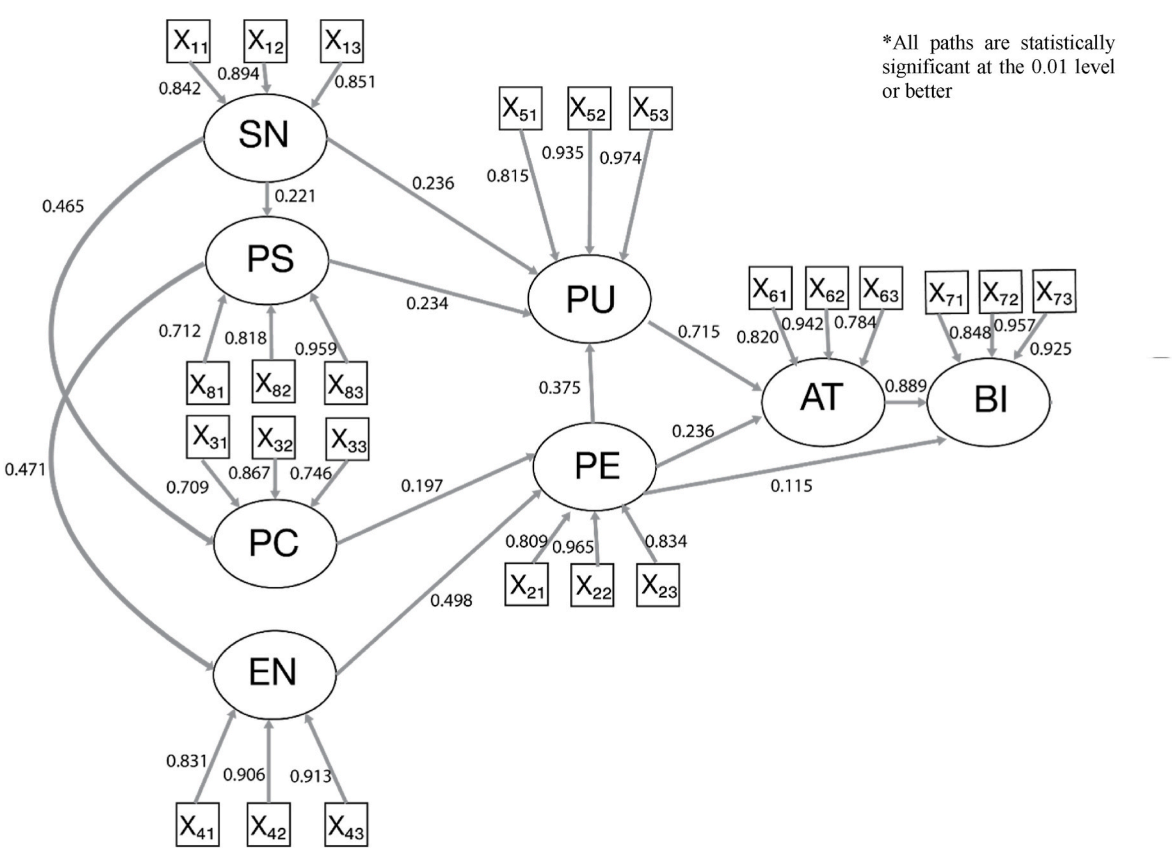


Fig. 7. Extended TAM SEM model fit with standardized estimate.

on the corresponding latent variable. All estimates range from 0.70 to upwards of 0.96.

In terms of the relationships between latent variables, all of the estimates are statistically significant at the 0.01 level. It can be observed that there are very strong direct relationships between the latent variables that make up the traditional TAM model (i.e., the model in Fig. 1). Perceived usefulness (PU) has a standardized effect of 0.693 on attitude towards participating (AT), while perceived ease of use (PE) has a much smaller effect of 0.215. The effect of perceived ease of use (PE) on attitude can be seen to be mostly mediated by perceived usefulness. This means that part of the perception of how easy something is to use is determined by how useful it is perceived to be. It is also noteworthy to observe that behavioural intention (BI) is almost solely directly affected by the user's attitude towards participation. For the external variables of social norm (SN), perceived ease of use (PE), perceived cohesion (PC) and perceived enjoyment (EN), the standardized effects range from 0.197 to 0.498. These effects can be added up as indirect effects to behavioural intention and this means that all external variables significantly indirectly affect behavioural intention.

The model structure contains several significant mediated indirect effects. These indirect effects are presented in Table 6. The largest indirect effects of social norm (SN) on behavioural intention (BI) are mediated by perceived usefulness (PU) and attitude towards participation (AT). The effect size is 0.150. Perceived security (PS) has an indirect effect mediated as well by perceived usefulness (PU) and attitude towards participation (AT); the effect size is 0.149. Perceived cohesion (PC) has indirect effects through several paths. The effect sizes range from 0.023 to 0.047. The effects of the shortest path are mediated by perceived ease of use (PE) only, while the longest path is mediated by perceived ease of use (PE), perceived usefulness (PU), and attitude towards participation (AT). Perceived enjoyment (EN) also has a similar indirect effect on behavioural intention (BI); the effect sizes range from 0.057, in the most direct path via perceived ease of use (PE), to 0.104 in the path mediated by perceived ease of use (PE), and attitude towards participating (AT). The indirect effects of perceived usefulness (PU) on behavioural intention (BI) are mediated by attitude towards participating (AT), with effect size of 0.635. Apart from the direct effect, perceived ease of use (PE) also has two different indirect mediated effects. The effect mediated only by attitude towards participating is

Table 6
Standardised direct, indirect and total effects on behavioural intention.

Attitudes and perceptions	Direct effects	Indirect effects		Total Effects
		Effects	Path	
Social norms (SN)	–	0.150[a]	PU, AT	0.235
	–	0.033	PS, PU, AT	
	–	0.011	PC, PE	
	–	0.019	PC, PE, AT	
	–	0.022	PC, PE, PU, AT	
Perceived security (PS)	–	0.149	PU, AT	0.281
	–	0.027	EN, PE	
	–	0.049	EN, PE, AT	
	–	0.056	EN, PE, PU, AT	
Perceived cohesion (PC)	–	0.047	PE, PU, AT	0.111
	–	0.023	PE	
	–	0.041	PE, AT	
Perceived enjoyment (EN)	–	0.119	PE, PU, AT	0.28
	–	0.057	PE	
	–	0.104	PE, AT	
Perceived usefulness (PU)	–	0.636	AT	0.636
Perceived ease of use (PE)	–	0.238	PU, AT	0.448
	–	0.210	AT	
Attitude toward playing (AT)	0.889	–	–	0.889

[a] The estimate of 0.150 is calculated by multiplying three path estimates, including SN◇PU (0.236), PU◇AT (0.715) and AT◇BI (0.889).

0.210, and the indirect effect mediated by both perceived usefulness (PU) and attitude towards participating (AT) is 0.238. Further, since the standardised estimates are reported for the SEM model, total effects can be calculated by sum up the indirect paths. Perceived usefulness (PU) has the largest total effects on behavioural intention (BI) and followed by perceived ease of use (PE).

The relationships between perceptions and behaviour intentions for the gamified scheme identified by the model are further discussed in the next section.

6. Discussion

Several implications can be drawn from the SEM model results. Different attitudes and perceptions are shown to have a statistically significant effect on behavioural intention that is believed to lead to actual behaviour change.

Direct effects show the direct relationships between the variables of the extended TAM. The main relationships to be identified are the direct relationship between perception variables (i.e. perceived usefulness, perceived ease of use, perceived cohesion, social norm, perceived security, and perceived enjoyment) and either behavioural intention or attitude towards participating. In particular, the direct relationship with behavioural intention is the critical link of interest to find since this link might refer to direct behaviour change. From the SEM model results, only one direct relationship can be found with behaviour intention. Ease of use of the scheme has a direct effect on behavioural intention and this relationship means that how easy it is to understand the scheme is a critical factor in making users adopt the gamified scheme. This relationship has been proven critical in previous studies (Ambrey & Yen, 2018; Yen et al., 2022). However, this direct effect is rather small compared to the direct effect between perception variables and attitude towards participating. In other words, those perception variables would all have indirect impacts on behavioural intention. This shows that having a positive attitude towards the scheme is the main factor that creates a positive behavioural intention.

The direct effect between perception variables and attitude towards participating is directly affected by perceived ease of use and perceived usefulness. Perceived ease of use has a larger direct effect on attitude towards the scheme than directly on behavioural intention. However, the main factor that affects attitude towards the scheme is perceived usefulness. This shows that when the target user perceives that the gamified scheme brings some sort of useful outcome (e.g., significant reward), the attitude towards participating in the scheme will be more favourable. Social norm and perceived security directly affect perceived usefulness with similar effect. This means that those two perception variables are equally important for perceived usefulness. This relationship also indicates that if users perceive the gamified scheme is socially accepted with personal information secured, they would then have a positive attitude towards participating and thus behaviour intention. Finally, perceived cohesion and perceived enjoyment directly affect perceived ease of use. The largest direct effect on perceived ease of use comes from perceived enjoyment. This means that a gamified scheme must be perceived as highly enjoyable in order for users to perceive that it is easy to use or accessible. A more enjoyable game would then result in a higher behaviour intention through attitude towards participating, which is consistent with the work by Ambrey and Yen (2018). Further, perceived enjoyment is not the most or principal perception since its total effect only accounts for 0.28. This result is not totally surprising: maybe gamified scheme introduces game elements but it is not a game. A gamified scheme needs to be a useful one to be able to attract participants as a prerequisite to changing behaviour. Perceived cohesion also affects perceived ease of use, which means that if a user feels a sense of belonging to a community or group, then the scheme will be perceived as easier to use. Hsu and Lu (2004) indicated that group members tend to follow a group norm as a result of two behavioural responses: informational influence and normative influence. The positive effect from perceived cohesion is in line with the literature that indicates cohesive groups (e.g., employees) exhibit greater conformity and a more coordinated pattern of behaviour (Moreland & Levine, 2014; Shah, 1998).

Apart from direct impacts, as mentioned earlier, there are multiple indirect impacts on behaviour intention. In this section, the three main indirect impacts are discussed. The largest indirect effect on behavioural intention is the effect of perceived usefulness on behavioural intention, which is mediated by attitude towards the scheme. This effect can be understood to mean that perceiving a gamified scheme as something that has utility or brings some reward to the user is the main source of a user's intention to participate in this scheme (Aguiar-Castillo et al., 2018). The second largest effect is perceived ease of use, which is mediated by perceived usefulness and attitude towards the scheme. This means that the perception of how easy it is to participate in the scheme is affected by how useful the user perceives a scheme to be, then followed by the indirect effect from social norm. The effect is mediated by perceived usefulness and attitude towards participating, which is also mediated by perceived usefulness and attitude towards the scheme. This means that a high social norm will create good behavioural intention to participate in the scheme as long as the users perceive the scheme provides expected usefulness (Berger & Schrader, 2016).

The success of gamified schemes depends on several factors that affect a user's attitude towards the scheme, as well as behavioural intention. Based on the model results, several policy implications can be drawn regarding the design of gamified TDM policies. First, for a user to adopt a gamified scheme, the most important factor is that users perceive they have something to gain from participating; having something to gain means there is perceived usefulness. The results of this study are in line with previous gamification research (Dikcius et al., 2021; Yang et al., 2017), which confirmed that perceived usefulness tends to have a strong indirect effect on behavioural intention. The usefulness can be discussed in two aspects, extrinsic and intrinsic motivation. In terms of extrinsic motivation, the usefulness mainly refers to reward types. This means that, when designing a gamification scheme, policy makers should pay close attention to the type of rewards offered; these rewards should be regarded as useful to create a positive attitude towards participation for target users. However, the design of the gamified scheme should pay attention to the 'overjustification' effect where intrinsic motivation is shifted towards the less desirable extrinsic motivation (Lepper et al., 1973; Yen et al., 2019). Therefore, some other studies have pointed out the importance of designing the gamified scheme by providing intrinsic motivation for users to perceive the scheme is useful. For instance, behaviours generally regarded as positive, such as being environmentally friendly (e.g., by using public transport not driving) and recycling, can create this kind of intrinsic motivation (Aguiar-Castillo et al., 2018).

Perceived ease of use is also an important factor to consider when designing gamified schemes. The results of this study show that if a scheme is too complicated, behavioural intention will directly decrease. This affirmation is supported by previous studies (i.e., Liu & Li, 2011; Mallat et al., 2009), which also found that perceived ease of use directly affects behavioural intention for gamified schemes where smartphone technology plays a key role. Similar findings can also be found in the transport field. Wang et al. (2020) had the same findings from a shared bike user survey that behavioural intention would be influenced by perceived ease of use. The results of this study find not only should a gamified scheme be easy to use but also enjoyable. Similar results can be found from previous research by Rodrigues et al. (2016); Venkatesh (2000). This indicates that policy makers should focus on creating an engaging and entertaining scheme to provide an enjoyable experience to users. Some examples of engaging gamification schemes can include the use of leader boards and level up systems (Coombes & Jones, 2016) or special rewards that require users to participate at certain hours to get special rewards (Bolderdijk et al., 2011).

The positive effects of perceived security on behavioural intention found in this study are also supported by previous research (Patel & Patel, 2018). Policy makers have to consider how a user's perception that their information is safe influences how a user would perceive a scheme to be useful. In recent years, people have generally become increasingly more cautious about internet security. Making sure users know their personal information or the rewards they have earned will not be hacked and stolen is an important aspect to increase behavioural intention.

Last but not least, social norm has an indirect effect on behavioural intention, mediated by perceived usefulness and attitude towards participation. These findings are supported by previous research on the effect of social norm, also referred to as subjective norm (Septiani et al., 2017), on perceived usefulness and behavioural intention. Social norm is often discussed when studying potential TDM policies. In many cultures, social pressure is the main factor in increasing the willingness to adopt new policies. Initiating a trend of public transport use through the use of gamified schemes is vital, since it may turn into a larger trend because people consider the expectations of others when choosing whether or not to take part (Zhang et al., 2016). Behavioural intention can thus be achieved through the popularization of the gamified scheme, because, as more people use the scheme, it will have a higher perceived usefulness due to social pressure, and lead to increased behavioural intention.

7. Conclusions and recommendations

7.1. Conclusions

Gamification is an emerging trend in the context of TDM policy instruments. It relies on positive incentives and motivations to achieve behavioural change. This study designed several gamified schemes to explore which perceptions and attitudes toward a gamified scheme influence user participation. These results confirm attitudes that are critical to participation and underline the importance to investigate such attitudes before designing a gamified TDM strategy. The SEM used in this study was based on an extended TAMand identified several key relationships, in line with previous literature that is not limited to gamification studies. The key perception of the extended TAM is that behavioural intention refers to actual use (e.g., join the scheme in this study). The results show how important attitude towards participation and perceived ease of use is for understanding behavioural intention with both these variables having significant direct effects. However, just as important are the indirect effects with perceived usefulness, perceived enjoyment, perceived security, perceived cohesion, and social norm having varying strengths of impact on behavioural intention. In particular, perceived usefulness is worthy of more attention by policy makers to design a more effective gamified scheme since perceived usefulness has the highest impact on behavioural intention.

Based on the SEM results, to have a successful gamification intervention, the scheme must be perceived as easy to use, to a degree where the target demographic will feel no burden in "giving it a try". Then when the user perceives it as useful, continued positive attitude and thus positive behavioural intention is achieved. This perceived usefulness should ideally come from the intrinsic motivation that appears from the convenience of using public transport. Behavioural intention may also be increased by improving perceived enjoyment. This would likely be achieved by making the gamified scheme something that people actually have fun using (e.g., add on game design) instead of just a means to an end (e.g., loyalty reward). This can be achieved by methods such as participatory planning, giving potential users a chance to have an input into how the gamified scheme can work to better suit their needs, through processes such as surveys, interviews, focus groups, user workshops, and co-design to actively involve stakeholders in the process of creating a gamified scheme.

7.2. Limitations

The complexity of the statistical model used for this study requires a fairly large sample size. The study had only 160 participants, which was not enough to accurately estimate the structural equation model through traditional methods. The final model was estimated through a bias-corrected factor score path analysis (BCFSPA). This is a relatively new method of estimating complex path models. Traditional SEM goodness of fit measures are not fully reliable when using this method. Suitable goodness of fit measures for the BCFSPA method are still being studied (Devlieger et al., 2019), and a reliable method to calculate them is yet to be developed.

7.3. Recommendations

Future research may increase the sample size to improve the robustness of the model significance. The minimum sample size for a structural equation model of the complexity of the one used in this study should be at least 200 to be sufficient for a regular structural equation model. A larger sample size would also allow further analysis of attitudes and perceptions for different subsets (e.g., male vs female) of the study sample, giving researchers and policy makers more insight into how to create a more personalized user experience for their scheme users, and providing a clearer picture of who should be the target demographic of a gamified scheme.

CRediT authorship contribution statement

Barbara T.H. Yen: Methodology, Conceptualization, Writing – original draft. **Corinne Mulley:** Methodology, Conceptualization, Writing – original draft. **Gerardo Meza:** Writing- Original draft, Modelling, Data collection.

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.

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