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INFLUENCE OF REDUCED AIR POLLUTION SOURCE EMISSION INFORMATION ON USER BEHAVIOURAL INTENTION TOWARDS E-SCOOTER PRODUCTS

ABSTRACT

In this study, a mobile application-based service providing information on the reduction in the air pollution source emissions due to the replacement of conventional scooters by electric scooters (e-scooters) was proposed to increase user awareness of air quality and purchase intention towards e-scooters. The extended unified theory of acceptance and use of technology was employed and an explanatory variable of environmental awareness (EA) was incorporated for enhancing constructs to investigate the factors that may influence the user acceptance of text-based mobile information on the reduced carbon emissions, in comparison with that of histogram-based mobile information on the reduction in emissions of six air pollution sources. A within-subjects experimental design was employed to evaluate both information contents. The results indicate that the model constructs of habit and EA are useful predictors of the behavioural intention (BI) to use app services. Furthermore, providing different mobile information contents demonstrated no statistically significant difference in the user's acceptance and intentions. However, providing different mobile information contents on the same information spindle may trigger different constructs and intensities of influence on users' purchase intentions for e-scooters. Based on these findings, several recommendations for app managers and developers and suggestions for future research have been provided.

1. INTRODUCTION

Air quality is closely linked to the Earth's climate and ecosystems globally. Furthermore, ambient air pollution is expected to potentially impact the global market, thereby leading to significant economic and healthcare costs in the next few decades [1]. The World Health Organisation indicated that the major ambient pollution sources include vehicles, power generation systems, building heating systems, industrial systems, and agriculture/waste incineration. Among these, road transport is a major source of harmful air pollutants [2]. Countries jointly establishing related policies to reduce air pollution may be lowering the burden of disease attributable to air pollution as well as contributing to the near- and long-term mitigation of climate change. To reduce the air pollution caused by fuel-powered scooters, the Taiwanese government has implemented a policy of purchase/replacement subsidy to encourage people to replace two-stroke/four-stroke scooters with electric two-wheelers (E2Ws) or cleaner scooters that meet the Phase-7 emission standards. The Pollution emissions are 0.12g/km for phase-7 scooters and 0.01g/km for electric scooters (e-scooters) [3]. Because providing E2W test ride services has a positive impact on the user acceptance level of the E2W product, many E2W manufacturers have launched free test ride services to promote their E2W products for Taiwanese consumers. Moreover, e-scooter products provide corresponding mobile application (app) services to the riders free of charge. The app services between the e-scooter product and the e-scooter owners/test riders are crucial in facilitating the rider-product interaction. The purpose of this study is to experimentally explore user acceptance using an app service, which contains information regarding the reduction in air pollution source emissions resulting from the replacement of conventional scooters with e-scooters, and understand the effect of the environmental information on user evaluation of the quality of their interaction with the app. This study also aims to analyse the user experience in receiving environmental information on an app, to understand the

factors that influence the acceptance of the mobile information. More precisely, the acceptance of the information on an app service is examined based on user response, from a human-system interaction perspective. Since potential consumers obtain the mobile information directly after the e-scooter test ride, an in-depth understanding of the factors that affect the adoption of the environmental information on the app is required to better understand and facilitate user acceptance. Another objective of this study is to further understand whether providing the proposed app service encourages user intentions for purchasing e-scooters.

1.1 Mobile technologies and information delivering

Smartphones are powerful devices in small mobile packages. Such mobile devices possessing advanced computing ability combined with wireless connectivity can achieve efficient searching, transmission, and processing of streamlined information. Moreover, smartphones have the ability to download and run multiple mobile apps, which are software programs containing a wide range of information and functions to serve a mobile user extensively according to the needs. Hence, apps are an integral part of the smartphone experience. Owing to the continuous evolution of app services, smartphones have become more versatile and prevalent. More specifically, according to Statista [4], approximately 3.5 billion smartphone users, which is 45.12% of the world's population, were expected around the world by 2020. With the ubiquity of smartphones, a large number of apps were developed for mobile users. As of the first quarter of 2019, there were more than 2.6 million Android and 2.2 million iOS apps that users can choose to download from Google Play and Apple's App Store, respectively [5]. Furthermore, app downloads are increasing significantly around the world. In 2017, approximately 178.1 billion apps were downloaded to mobile devices and this number is expected to increase to 258.2 billion by 2022, which will represent an increase of 45% [6]. Meeker [7] indicated that approximately 33% of the total media usage time is spent on apps via mobile devices by end-users. In other words, mobile users spend more time using apps than any other type of software program at present.

In this study, mobile technologies were used as a medium to deliver content about the reduced amounts of air pollution source emissions when replacing a conventional scooter ride with that of an e-scooter. This was achieved through an app to increase user awareness about the internet of things (IoT) technology and environmental concerns, and subsequently to develop positive intentions toward the purchase of e-scooters. This is the part of the riding experience process when commuters are using an e-scooter product and app service. Previous studies verified that one of the main factors in determining the extent of EA is access to information [8–10], especially via mobile technologies [11]. Furthermore, a general trend toward higher environmental consciousness over the past decades has been observed. The rise in EA changes the consumer behaviour. For example, in the US, the Beijing Building Materials Group conscious consumer report shows that 67% of Americans consider that it is important to buy products with environmental benefits and 51% are willing to pay more for such products [12]. The US marketplace for natural products grew 25% between 2006 and 2008 [13]. In Europe, 75% of Europeans were reported as ready to buy environmentally friendly products even if the cost is slightly higher than other products [14]. As not all the apps are successful in the market, identification of the factors influencing the intention of app usage can provide app developers, marketers, and researchers with important information about the decision process of app usage intention [15].

1.2 Extended unified theory of acceptance and use of technology (UTAUT2) model

Various theoretical models have been proposed to predict the adoption and use of technology. Among them, UTAUT2 was identified as a theoretical foundation for proposing the conceptual model utilised in determining Taiwanese consumer adoption and intention of the proposed app service. UTAUT2 [16] was extended from UTAUT, which is a framework devised by Venkatesh et al. [17] to predict workplace technology acceptance. UTAUT2 claims the variables, including performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FCs), hedonic motivation (HM), price value (PV), and habit (HA), are the main constructs in influencing consumer behavioural intention (BI) towards information technology use [16]. More specifically, PE is defined as the extent of benefits that a technology can provide to the consumers while performing certain activities [17]. Previous research

has found that users are willing to download apps because they learn values and innovations from the apps [18]. Therefore, the PE construct is considered to be one of the core predictors of the intention to adopt a technology. EE is defined as the degree of ease that is associated with consumer use of technology [17]. It indicates an extrinsic motivation related to utility. Users tend to prefer technology that is easy to learn and understand and that has maximum efficiency. Therefore, EE focuses on the user-perceived acceptance of a new behaviour while using a new technology in the early stages. FCs refer to consumer perception of the resources and the support that is available to perform a behaviour [19]. FCs are external factors that reflect an individual's perception of control over his/her behaviour. SI is defined as the extent to which an individual cares about the opinions and perceptions of others who are important [16]. SI is also a determinant in the unique feature of mobile internet via mobile devices [20] and in app usage [21]. HM represents the extent to which consumers believe that using a technology is entertaining [16]. HM is conceptualised as intrinsic utilities, such as user-perceived joy, fun, playfulness, entraining, and enjoyment. Therefore, HM is an important determinant of technology acceptance and use. PV is defined as the consumers' cognitive trade-off between the perceived benefits of the application and the monetary costs for using them [16]. Consumers typically bear the expenses themselves. Price issues were found to be critical and received particular interest from customers when they were in the process of accepting or rejecting technologies. However, Taiwanese e-scooter manufacturers provide app services free of charge. Hence, the concept of PV was found to be irrelevant and was thus removed from the core model. HA is defined as the extent to which people tend to perform behaviours automatically through learning [22]. With the rapid growth in the development of apps, most users may acquire the habit of app usage from the repetitive use of multiple apps via mobile devices. Therefore, the concept of HA may be relevant to the core model.

An explanatory variable of EA is incorporated for enhancing constructs to predict user intentions in receiving the environmental information on the proposed e-scooter app service and purchasing an e-scooter. EA is defined as the emergence of environmental sensitivity through the conscious perception of environmental problems by the individual, and by behaving accordingly and taking precautions to protect the environment [16]. A high level of EA is expected to be a critical prerequisite for long-lasting environmental protection, and thus plays a critical role in long-lasting reductions in environmental impacts [23]. This is because behaviours of the individuals against the environment result from a reflection of their EA [24]. Therefore, it is important to measure an individual's ability to understand the nature of environmental processes and problems, his/her degree of concern for the current status of environmental quality, and the extent to which he/she is committed to participating in environmental activities [25, 26]. Furthermore, a general trend towards higher environmental consciousness has been observed over the past decades. The rise in EA has led to changes in consumer behaviour.

Individual differences—age, gender, and experience—are assumed to moderate the effects of constructs on BI and technology use. UTAUT2 has been used to understand the intentions and acceptance of mobile app use (e.g. Madigan et al. [27]).

2. METHODS

2.1 Measurements

A mixed-methods, repeated measures study was conducted using a laboratory-based experimental design. This study provides two types of content to display: the reduced amounts of air pollution source emissions for each e-scooter ride in the app (please refer to *Figure 1*), and two 360° immersive videos streaming an e-scooter ride in the mountains at a speed of 40 km/h. The two information types were designed on the app: (1) text-based information on the reduction in the amounts of carbon source emissions by replacing scooters with e-scooters; and (2) histogram-based information on the reduced amounts of air pollution source emissions by replacing scooters with e-scooters. The previous study verified that using virtual reality (VR) technology, such as fully immersive VR and desktop VR, in watching 360° panoramic videos may create reality-like scooter riding experiences for users (e.g. Huang [28]). The two scenes were designed to ride the same e-scooter on the same mountain road with the same speed and on different sections. The fact that the mountain scenery is not very different can reduce the bias
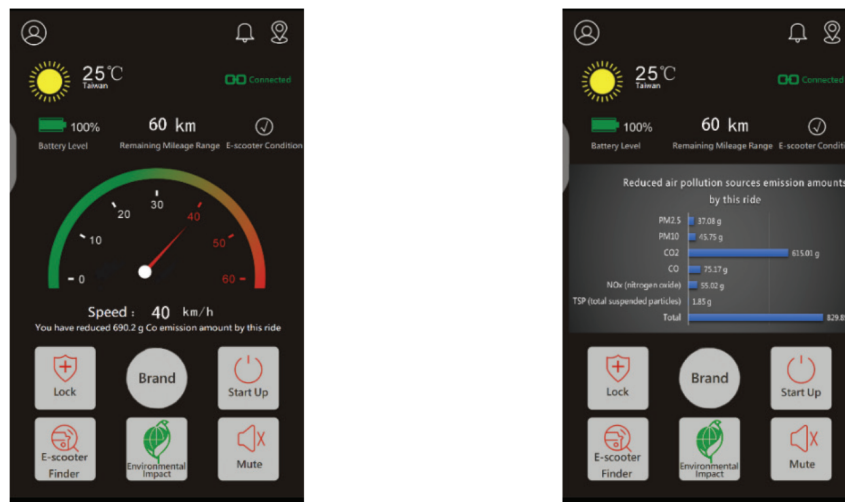
a) Text-based information stating "You have
saved 690.2 g of CO emissions by this ride"

b) Histogram-based information stating "Saved air
pollution source emissions by this ride"

Figure 1 – Screenshots of two different types of information designed in the app

caused by the experiment. Participants undertook an e-scooter riding scene, and provided a subjective rating following each trial procedure. To counter the effects of the experimental sequence, the participant sample was counterbalanced and tested over two distinct phases. In Phase 1, half of the participants used the text-based information, while the other half used histogram-based information. In Phase 2, participants were exposed to the alternative trial procedure. Individual participation in Phases 1 and 2 occurred on the same day. The study was approved by the Research Ethics Committee of the National Tsing Hua University (IRB protocol number 10806EC061).

The subjective rating of using text-based carbon information was designed to explore participants' acceptance of the reduced carbon source emissions (in grammes) by riding the e-scooter, while that of using histogram-based information was designed to explore the acceptance of the reduced emission amounts of greenhouse gases, including $PM_{2.5}$ (particulate matter 2.5 micrometres or less in diameter), PM_{10} (particulate matter 10 micrometres or less in diameter), CO_2 (carbon dioxide), CO (carbon monoxide), NO_X (nitrogen oxide), and TSP (total suspended particles), by riding the e-scooter. More specifically, the subjective rating in the case of using text-based carbon information contained three sections— (1) personal information: three items designed to collect socio-demographic data on gender, age, and transport mode (scooter, E2W, bike, public transport, car, and other); (2) UTAUT2: twenty-six items (see *Table 1*) designed to measure the PE, EE, SI, FC, HM, HA, EA, and BI, assessed on a 7-point Likert scale, ranging from very strongly agree to very strongly disagree; and (3) purchase intention (PI): one item designed to collect quantitative data on whether the participant perceived more willingness to purchase an e-scooter product. In addition, the subjective rating in the case of using histogram-based information contained UTAUT2 and PI sections.

2.2 Participants

Sixty-four individuals (32 males and 32 females) participated in the experiment and completed the surveys. The participants' median age was 21 years (min: 20, max: 28). Participation was rewarded with a non-monetary compensation of a wired headset (costing 5 USD). The demographic information of the respondents is shown in *Table 2*.

Analyses were conducted using the SPSS software, Version 22.0, and SPSS Amos software, Version 20.0. Variables were assessed by the measurement model assessment, hierarchical multiple regression analysis, chi-square test, and Wilcoxon signed ranks test. The two-tailed significance level was set at $p < 0.05$.

3. RESULTS

Table 1 – Constructs and measurement instruments for app service

Construct	Items
PE	PE1. I find air pollution information from the app useful.
	PE2. Using the app helps me understand the environmental benefits for e-scooter products more quickly.
	PE3. Using the app increases my understanding of e-scooter products.
	PE4. I can easily find features of the e-scooter in terms of environmental benefits in the app.
EE	EE1. Learning how to use the app is easy for me.
	EE2. My interaction with the app is clear and understandable.
	EE3. It is easy for me to become skilful at using the app.
	EE4. I find the app easy to use.
SI	SI1. People whose opinions I value prefer that I use the app.
	SI2. People who are important to me think that I should use the app.
	SI3. People who influence my behaviour think that I should use the app.
FC	FC1. I have the knowledge necessary to use the app.
	FC2. I can get help from others when I have difficulties using the app.
	FC3. I have the resources necessary to use the app.
HM	HM1. Using the app is fun.
	HM2. Using the app is very entertaining.
	HM3. Using the app is enjoyable.
HA	HA1. I am addicted to using the app.
	HA2. The use of the app has become a habit for me.
	HA3. I must use the app.
EA	EA1. The app facilitated for me to value the environmental benefits of E2Ws.
	EA2. I will be willing to pay more attention to environmental protection in daily commuting selections.
	EA3. I will be willing to pay more attention to air quality in daily commuting selections.
BI	BI1. I intend to continue using the app in the future.
	BI2 I will always try to use the app in my daily life.
	BI2. I plan to continue to use the app frequently.

Table 2 – Demographic information of the respondents

Item		Frequency (*N*)	%
Gender	Female	32	50.0
	Male	32	50.0
Age	20	17	26.6
	21	34	53.1
	22	10	15.6
	23	1	1.6
	26	1	1.6
	28	1	1.6
Transportation usage	Public transportation	36	42.2
	Scooter	27	56.3
	Car	1	1.6

The user agreement levels related to e-scooter purchasing intention after using the text-based carbon information ($\bar{X}$=4.53, σ=1.04) and histogram-based information ($\bar{X}$=4.56, σ=1.19) were slightly aligned. Approximately 35 participants (54.7%) agreed that using the text-based carbon information might enhance their intention to purchase an e-scooter product, whereas 37 participants (57.8%) believed that using the histogram-based information might enhance their intention to purchase an e-scooter product.

3.1 Measurement model assessment

Both text-based carbon information and histogram-based information resulted in high internal consistencies of the construct scores (please refer to *Table 3* for scale reliabilities). In addition, the

Mardia's multivariate normality test [21] revealed an acceptation of the multivariate normality assumption in obtaining text-based information (Mardia'scoefficient = 119.443; critical ratio = 12.521; p·(p+2) = 728) and histogram-based information (Mardia's coefficient = 104.212; critical ratio = 10.924; p·(p+2) = 728). Furthermore, SRMR values<0.8 can be considered as good fit [29]. The sampling for using text-based information (SRMR value=0.0798) and histogram-based information (SRMR value=0.0765) was adequate.

A standardised factor loading should be greater than 0.5 and less than 0.95 for better results. Typically, factor loadings greater than 0.5 are considered acceptable, whereas those above 0.7 are considered good [30]. However, factor loadings exceeding 0.95 are called "offending estimates", which will cause the residual error to be insignificant. It is caused by too high correlation, that is, some question items are repeated. The item should be deleted [31]. *Table 3* indicates that the item EA1 on using histogram-based information was excluded in the subsequent analyses because it exhibited a factor loading of less than 0.5. In addition, the items SI2, SI3, and BI3 on using histogram-based information were excluded in the subsequent analyses because they exhibited factor loadings greater than 0.95. Other items were loaded appropriately. In the confirmatory factor analysis, the convergent validity is based on the composite reliability (CR), and the construct validity is based on the average variance extracted (AVE). In *Table 3*, all values of the CR and AVE for

Table 3 – M(mean), SD(standard deviation), Loadings (Standard item loadings), CR, and AVE

Construct and item		Text-based information						Histogram-based information					
		M	SD	Loadings	α	CR	AVE	M	SD	Loadings	α	CR	AVE
PE	PE1	5.00	0.96	0.798	0.857	0.86	0.78	5.11	1.01	0.936	0.859	0.86	0.79
	PE2	4.69	0.97	0.725				4.66	0.96	0.714			
	PE3	5.08	0.93	0.795				5.03	1.05	0.786			
	PE4	5.23	0.85	0.789				5.33	1.05	0.684			
EE	EE1	5.03	1.15	0.524	0.837	0.85	0.77	4.91	1.19	0.498	0.839	0.89	0.86
	EE2	5.19	0.96	0.925				5.16	1.03	0.826			
	EE3	5.06	1.02	0.867				4.94	1.19	0.825			
	EE4	5.08	1.07	0.714				5.28	1.00	0.924			
SI	SI1	4.81	1.10	0.843	0.938	0.85	0.92	4.83	1.18	0.936	0.941	0.94	0.92
	SI2	4.89	1.13	0.956				5.06	1.13	0.887			
	SI3	4.95	1.13	0.951				4.98	1.18	0.930			
FC	FC1	5.11	0.86	0.805	0.806	0.82	0.77	4.95	1.01	0.765	0.777	0.78	0.73
	FC2	5.31	0.92	0.735				5.47	0.89	0.726			
	FC3	5.02	0.98	0.778				4.97	1.07	0.705			
HM	HM1	4.55	1.18	0.884	0.934	0.93	0.91	4.28	1.17	0.856	0.905	0.91	0.87
	HM2	4.67	1.13	0.931				4.39	1.06	0.915			
	HM3	4.61	1.16	0.908				4.41	1.22	0.848			
H	H1	4.47	1.14	0.873	0.852	0.86	0.82	4.55	1.15	0.916	0.874	0.88	0.84
	H2	4.36	1.12	0.804				4.17	1.20	0.857			
	H3	4.72	1.02	0.771				4.73	1.06	0.754			
EA	EA1	4.81	0.94	0.835	0.883	0.89	0.87	5.02	1.06	0.871	0.900	0.91	0.88
	EA2	4.73	1.20	0.849				4.89	1.07	0.867			
	EA3	4.77	1.11	0.873				4.94	1.11	0.861			
BI	BI1	4.25	1.18	0.719	0.886	0.81	0.83	4.23	1.21	0.827	0.916	0.90	0.87
	BI2	4.66	1.10	0.920				4.67	1.16	0.883			
	BI3	4.61	1.06	0.956				4.66	1.06	0.936			

Table 4 – Correlations and values of square root of AVE (using text-based information)

	PE	EE	SI	FC	HM	H	EA	BI
PE	0.883							
EE	0.689**	0.877						
SI	0.633**	0.361**	0.959					
FC	0.595**	0.491**	0.384**	0.877				
HM	0.649**	0.537**	0.421**	0.464**	0.954			
H	0.542**	0.232	0.737**	0.326**	0.438**	0.906		
EA	0.580**	0.453**	0.393**	0.615**	0.610**	0.419**	0.933	
BI	0.522**	0.298*	0.613**	0.344**	0.481**	0.764**	0.605**	0.911

*Notes: * p < 0.05; ** p < 0.01; Diagonal elements are the values of square root of AVE and off-diagonal elements are correlations*

Table 5 – Correlations and values of square root of AVE (using histogram-based information)

	PE	EE	SI	FC	HM	H	EA	BI
PE	0.889							
EE	0.768**	0.927						
SI	0.564**	0.438**	0.959					
FC	0.703**	0.745**	0.473**	0.854				
HM	0.538**	0.521**	0.340**	0.573**	0.933			
H	0.632**	0.529**	0.355**	0.647**	0.771**	0.917		
EA	0.619**	0.466**	0.528**	0.558**	0.577**	0.789**	0.938	
BI	0.551**	0.391**	0.620**	0.477**	0.537**	0.728**	0.827**	0.933

*Notes: ** p < 0.01; Diagonal elements are the values of square root of AVE and off-diagonal elements are correlations*

the constructs exceed the criterion of 0.7, which represents good convergent and construct validities [22]. Furthermore, the square root of AVE for each factor for using both text-based information (as presented in *Table 4*) and histogram-based information (as presented in *Table 5*) is larger than the correlation coefficients of other factors, confirming sufficient discriminant validity.

3.2 Hierarchical multiple regression analysis

Hierarchical multiple regressions were used to predict two models: BI towards using text-based carbon information (Y_1) and BI towards using histogram-based information (Y_2). In each analysis, variables were entered in three steps: (1) the predictor variables (PE, EE, SI, FC, HM, HA, and EA); (2) the moderator variables (age and gender); and (3) the interaction terms for moderation analysis. Results indicated that none of the predicted moderated relationships reached significance for either Y_1 or Y_2. *Table 6* lists the main predictor variables (excluding interactions) for Y_1 and Y_2. In model Y_1, R^2 was significant in step 1 (F (7, 56)=18.034, p<0.001), accounting for 69.3% of the variance, whereas in step 2, the change in R^2 was not significant (F (2, 54)=3.085, p>0.05). This indicated that the second set of predictors could not predict BI. In addition, in model Y_2, R^2 was significant in step 1 (F (7, 56)=26.834 p < 0.001), accounting for 77.0% of the variance, whereas in step 2, the change in R^2 was not significant (F (2, 54)=2.470, p>0.05).

Hierarchical multiple regressions were used to predict two more models: user-perceived EA when using text-based carbon information (Y_3) and that when using histogram-based information (Y_4). The results indicated that none of the predicted moderated relationships reached significance for either Y_3 or Y_4. *Table 7* lists the main predictor variables (excluding interactions) for models Y_3 and Y_4. In model Y_3, R^2 was significant in step 1 (F (7, 56)=13.326, p<0.001), accounting for 62.5% of the variance, whereas the change in R^2 was not significant in step 2 (F (2, 54)=0.534, p>0.05). This indicated that the second set of predictors could not predict EA. In ad-

Table 6 – Hierarchical multiple regression results for Y_1 and Y_2

Model	Step		Step 1 β	Step 1 VIF	Step 2 β	Step 2 VIF	R^2	ΔR^2
Y_1	1	PE	-0.027	3.617	-0.070	3.683	0.693	0.654***
		EE	0.028	2.133	0.008	2.147		
		SI	0.074	2.660	0.024	2.742		
		FC	-0.126	1.897	-0.102	2.019		
		HM	0.006	2.098	0.049	2.161		
		H	0.585***	2.457	0.613***	2.487		
		EA	0.408***	2.124	0.382**	2.191		
	2	Age			0.061	1.095	0.724	0.678
		Gender			0.185*	1.148		
Y_2	1	PE	-0.045	3.488	-0.064	3.660	0.770	0.742***
		EE	-0.048	3.190	-0.087	3.449		
		SI	0.344***	1.762	0.337***	1.765		
		FC	-0.111	2.945	-0.119	3.031		
		HM	-0.040	2.639	-0.044	2.651		
		H	0.388*	5.147	0.433**	5.251		
		EA	0.475***	3.366	0.464***	3.411		
	2	Age			-0.050	1.221	0.790	0.755
		Gender			0.136*	1.117		

*Notes: * p < 0.05, ** p < 0.01, *** p < 0.001; VIF (variance inflation factor)*

Table 7 – Hierarchical multiple regression results for Y_3 and Y_4

Model	Step		Step 1 β	Step 1 VIF	Step 2 β	Step 2 VIF	R^2	ΔR^2
Y_3	1	PE	0.085	3.600	0.099	3.675	0.625	0.578***
		EE	-0.001	2.136	0.000	2.147		
		SI	-0.083	2.660	-0.077	2.728		
		FC	0.362**	1.599	0.378**	1.668		
		HM	0.261*	1.917	0.252*	1.998		
		H	-0.179	3.487	-0.187	3.756		
		BI	0.498***	2.593	0.509**	2.922		
	2	Age			0.064	1.097	0.632	0.571
		Gender			-0.057	1.263		
Y_4	1	PE	0.111	3.444	0.100	3.635	0.770	0.741***
		EE	-0.023	3.198	0.012	3.484		
		SI	0.049	2.268	0.039	2.298		
		FC	0.024	2.996	0.043	3.090		
		HM	-0.068	2.626	-0.068	2.640		
		H	0.404**	5.094	0.367*	5.542		
		BI	0.475***	3.371	0.497***	3.657		
	2	Age			0.065	1.214	0.774	0.737
		Gender			-0.032	1.200		

*Notes: * p < 0.05, ** p < 0.01, *** p < 0.001; VIF (variance inflation factor)*

dition, in model Y_4, R^2 was significant in step 1 ($F_{(7, 56)}=26.780$, $p<0.001$), accounting for 77.0% of the variance, whereas in step 2, the change in R^2 was not significant ($F_{(2, 54)}=0.533$, $p>0.05$).

Finally, hierarchical multiple regressions were used to predict another two models: PI for e-scooters after using text-based carbon information (Y_5) and that after using histogram-based information (Y_6). The results indicated that none of the predicted moderated relationships reached significance for either Y_5 or Y_6. *Table 8* lists the main predictor variables (excluding interactions) for models Y_5 and Y6. In model Y_5, R^2 was significant in step 1 ($F_{(8, 55)}=9.894$, $p<0.001$), accounting for 59.0% of the variance, whereas the change in R^2 was not significant in step 2 ($F_{(2, 53)}=0.423$, $p>0.05$). This

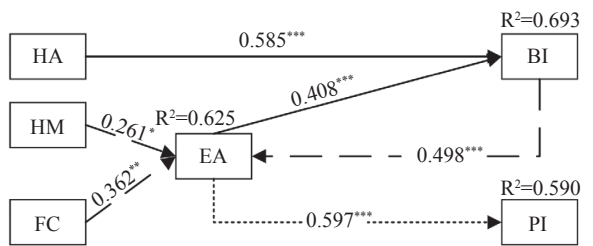*Table 8 – Hierarchical multiple regression results for Y_5 and Y_6*

Model	Step		Step 1		Step 2		R^2	ΔR^2
			β	VIF	β	VIF		
Y_5	1	PE	-0.041	3.620	-0.023	3.701	0.590	0.530***
		EE	-0.002	2.136	0.006	2.147		
		SI	0.111	2.678	0.131	2.744		
		FC	0.194	1.949	0.179	2.057		
		HM	0.118	2.098	0.097	2.170		
		H	0.113	3.572	0.072	3.851		
		BI	-0.214	3.254	-0.168	3.626		
		EA	0.597***	2.666	0.596***	2.718		
	2	Age			-0.058	1.108	0.596	0.520
		Gender			-0.073	1.272		
Y_6	1	PE	0.476**	3.497	0.550***	3.679	0.697	0.652***
		EE	-0.084	3.200	-0.088	3.485		
		SI	0.183	2.278	0.161	2.305		
		FC	-0.095	2.999	-0.111	3.098		
		HM	0.060	2.646	0.081	2.660		
		H	0.206	5.803	0.119	6.141		
		BI	0.252	4.354	0.347*	4.753		
		EA	-0.028	4.348	-0.037	4.433		
	2	Age			-0.204*	1.205	0.735	0.685*
		Gender			-0.072	1.233		

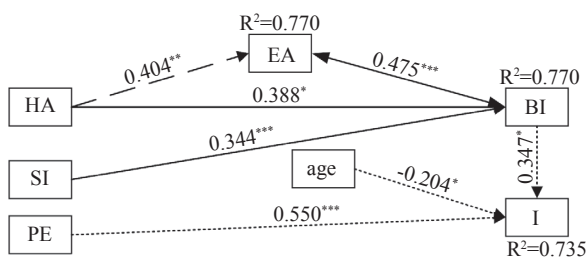*Notes: * p < 0.05, ** p < 0.01, *** p < 0.001; VIF (variance inflation factor)*

indicated that the second set of predictors could not predict PI. In addition, in model Y_6, R^2 was significant in step 1 (F (8, 55)=15.786, p<0.001), accounting for 69.7% of the variance, whereas in step 2, there was an improvement over the earlier model,

with an R^2 change of 0.735. Therefore, the change in R^2 was significant (F (2, 53)=3.801, p<0.05), indicating that the second set of predictors (age) could predict PI.

The structural models were tested using hierarchical multiple regression analysis, and the results are depicted in *Figure 2*.

3.3 Wilcoxon signed ranks test

The Wilcoxon signed-rank test is a non-parametric statistical hypothesis test used to compare two repeated measurements on a single sample to assess whether their population mean ranks differ. The results of this test indicated a significant difference in EA between text-based carbon information and histogram-based information (Z=–2.269, p<0.05, effect size (r)=0.244). Specifically, histogram-based information was found to result in a higher level of user-perceived EA (median=5) in comparison with text-based carbon information (median=4).

4. DISCUSSION

In this study, a quantitative analysis of the user-perceived BI and PI on using the information regarding the reduced air pollution on the mobile app while riding an e-scooter was conducted. The

a) Using text-based carbon information

b) Using histogram-based information

Figure 2 – Result of the structural model

effects of text-based carbon information and histogram-based information on user experience and acceptance upon obtaining air pollution information from the mobile app were investigated. Based on our findings, we further discuss the BI towards the information usage and PI for e-scooters.

4.1 Behavioural intention towards air pollution information on the app

Text-based carbon information

The results revealed that approximately 34.3% of the participants exhibited a positive BI towards using text-based information. In addition, two of the predicted relationships of model Y_1 were supported by HA and EA, both contributing uniquely and positively to the users' BI (please refer to *Figure 2a*).

HA is the strongest predictor, suggesting that the user-perceived HA reflected on using text-based carbon information on the app service is the most important factor influencing BI. More specifically, getting accustomed to, getting addicted to, or having a natural response to receiving text-based carbon information are important for users. HA is learned through repeated responses, thereby forming context-response associations in the memory. In other words, HAs are learned as automatic responses with specific features [32] and can be activated in the memory in an autonomous manner without requiring executive control [33]. Approximately 56.2% of the participants agreed to the aspects of HA. This implies that participants need to have extensive experience in using text-based information, which requires sufficient time for them to formulate a habitual behaviour towards the app. However, all the participants were using the text-based mobile information for the first time. Therefore, the HAs may have resulted from the repetitive use of mobile devices in contexts outside of the e-scooter app service, as the mechanisms to deliver efficient information services using the IoT technology on the app are structurally similar to those of most industrial contexts. The mobile users with strong HAs of app usage immediately thought of using the needed function and information when exposed to network environments that they were typically accustomed to. Once the users observe familiar indications from the app environment, habitual responses are activated. At this time, the users can act on the response in their mind spontaneously. With the global trend of the ubiquity of smartphones, using mobile apps to receive service and information has become a natural response for mobile users. Hence, under circumstances of affordable development costs and availability of technical capabilities, it is recommended that indications similar to network environments be directly designed on the vehicle dashboard or key to activate the rider's habitual responses of app usage.

The strong impact of EA on BI highlights the need to provide the environmental benefit of each e-scooter ride through an appropriate text content on the e-scooter app, so as to enhance users' environmental sensitivity. More specifically, understanding the environmental benefits of e-scooters, learning their contribution to environmental protection, and assisting in paying more attention to air quality are important for users. That is because EA is the attitude regarding the environmental consequences of human behaviours [34]. The results revealed that approximately 57.8% of the participants agreed to the aspects of EA. We further investigated the influences of user-perceived EA. Results indicated that the strong impact of BI on EA emphasises the importance of intention to obtain the text-based carbon information on the app, which may facilitate mobile users to develop their awareness of the environment and their connections to it and then towards the development of EA. FC is another significant factor in predicting EA. The FC construct is the extent to which an individual perceives that the organisational and technical infrastructures needed to use the intended system are available [35]. The positive impact of FC on EA highlights the need to supply resources through an appropriate human-computer interface and mobile devices, to promote easy and effective interaction and communication. In current mobile environments, resources, such as compatible technology and knowledge regarding smartphone operation, are available to mobile users. In this study, the text-based carbon information was applied in the E2W industry and real-time information was displayed on mobile devices that were familiar to users from other contexts, thereby mitigating some of the barriers of adoption, and consequently influencing their EA. Furthermore, HM had a positive impact on EA, emphasising the importance of users' sense of entertainment in developing their awareness of environmental protection via app services. Approximately 48.4% of the participants agreed to the aspects of HM. HM is a form of intrinsic motivation, such as fun, joy, enjoyment, entertainment, or pleasure while using a technology for the sake of

technology. In the case of hedonic technology comprising novelty seeking and uniqueness, the impact of intrinsic motivation may become more effective [36]. This implies that the likelihood of developing or enhancing EA may reach a higher level among users who perceive further intrinsic motivation in using popular mobile channels.

Histogram-based carbon information

The results revealed that approximately 43.7% of the participants exhibited a positive BI towards using histogram-based information. In model Y_2, HA, SI, and EA contributed positively to BI (please refer to *Figure 2b*).

SI is the strongest predictor, suggesting that the way in which users believe that others will perceive them as a result of having received the histogram-based information is the most important factor influencing BI. According to the SI theory, SI has an impact on individual behaviour [37], social behaviour [38], and decision making [39] through three mechanisms: compliance, identification, and internalisation. These three social processes are often represented by subjective norm, social identity, and group norm, respectively [40, 41]. The SI constructs are similar to these social processes. The results can be interpreted as the interest of the users in the opinions and attitudes of their reference groups, the sense of belonging and the maintenance of a satisfying relationship with the reference person or group, and the congruence of their values with those of the reference group members in formulating their intention to adopt the histogram-based information on the app. Approximately 68.7% of the participants agreed to the aspects of SI. This implies that the acceptance of the text-based carbon information by the reference group members surrounding the consumers may play a dynamic role in contributing to consumers' intentions towards mobile technology and environmental information. Moreover, the app in this experimental environment was set in voluntary contents. The results also further validated that SI in voluntary contexts has a direct effect on BI. Hence, app designers and managers should develop participation mechanisms to encourage users to actively share information using their e-scooter app, to enhance their intrinsic utilities and accelerate their intention to adopt the app. When users feel a sense of togetherness, closeness, and belonging towards their reference groups during the use of mobile information, they are more likely to exhibit

a higher BI. Consequently, providing high levels of SI may be regarded as the most important goal for the e-scooter app managers to gain BI.

The results revealed that the SI exhibited a moderately positive correlation with the HA. The positive impact of the HA on the BI emphasises the importance of users believing that the behaviour of receiving environmental information in the app is natural. A behaviour may become a spontaneously automatic response triggered by a specific indication in the environment through satisfactory repetition [42]. The results indicated that approximately 56.3% of the participants agreed to the aspects of HA. This implies that habituation is a quality that may be achieved through repeatedly performed behaviours. In other words, HA may determine the occurrence of future behaviour.

In contrast, there was a significant indirect effect between HA and BI, with EA fully mediating the relationship between HA, i.e., getting accustomed to, getting addicted to, or having a natural response to receiving the histogram-based mobile information, and the subsequent levels of BI. These findings indicate that the user's understanding of the environmental benefits of e-scooters, understanding of the contribution to environmental protection, and attention related to air quality form a significant pathway by which the user's automatic responses on receiving histogram-based mobile information affect the subsequent BI over time. In other words, there is a significant interaction and positive influence between EA and BI. In the latter part of the 20th century, increasing attention has been paid to environmental sustainability, which may have led people to create general perceptions regarding having a responsibility to ensure reduction in greenhouse gas emissions. This may be the reason why approximately 76.6% of the participants agreed to the aspects of EA. EA is an important pathway through which HA positively affects BI. Consequently, providing high levels of HA to achieve the highest EA may be regarded as an important objective for the e-scooter app managers to achieve BI.

4.2 Purchase intentions for e-scooters

Approximately 54.69% of the participants exhibited a positive PI when using text-based information, while approximately 57.8% of participants exhibited a positive PI when using histogram-based information.

In model Y_5, EA contributed positively to PI. EA was the strongest predictor, suggesting that providing text-based mobile information for users to apply in their daily commuting choices, so as to create environmental sensitivity in them, is the most important factor influencing intentions to purchase e-scooters. The results verified that in the case of providing text-based mobile information after each e-scooter ride, EA is a key construct in determining the adoption and eventual purchase of e-scooters. Previous studies have demonstrated that as the consumers' EA grows, the number of individuals willing to pay higher prices for eco-friendly products also increases [43, 44]. Additionally, the consumers' EA is directly related to the profit of environmental product manufacturers [45]. On the contrary, if consumers are not willing to pay higher prices for the environmental benefits to cover the additional costs, governments may have to subsidise these consumers who have paid the premium price to promote the consumption of eco-friendly products. The results revealed that approximately 57.8% of the participants agreed to the aspects of EA. EA and behavioural change can be promoted and strengthened through information design [46]. Hence, developing a suitable content to display simple and comparable text-based carbon information for assisting users to comprehend the environmental benefits, such as the amount of carbon emissions saved by replacing scooters with e-scooters, is suggested in a future study to enhance users' level of EA while using the app over time.

In model Y_6, BI and PE contributed positively to PI, while age contributed negatively. This implies that PE is the strongest predictor, suggesting that users' expected benefits obtained by using histogram-based mobile information is the most important factor influencing their intentions to purchase e-scooters. More specifically, providing useful histogram-based mobile information, understanding the characteristics of an e-scooter product, and assisting users in making particular e-scooter purchase decisions by the app service are important for the users. In other words, if a user perceives that the use of the histogram-based mobile information will contribute meaningfully in enhancing his/her e-scooter product cognition and assisting his/her purchase decisions, he/she may be willing to purchase e-scooters. This study verified that PE is the primary focus of the construct in determining the adoption and eventual purchase of an e-scooter. Approximately 68.75% of the participants agreed with the extent of perceived usefulness and

extrinsic motivation in using histogram-based mobile information. The levels of user-perceived PE may directly affect the user's decision to adopt e-scooters. It is an important objective for the app managers and designers to achieve the highest PE to gain PI. Therefore, enhancing relevant content, such as environmental benefits and e-scooter product features, and adding app service interaction designs are suggested to improve users' cognitive experience on the app service and awareness of e-scooter products. The manufacturers may enhance the e-scooter app services through their promotion to the public by demonstrating the significantly beneficial features. In addition, the positive impact of BI on PI emphasises the importance of users' willingness and intention to use the histogram-based information on the app in influencing their intentions to purchase an e-scooter. It is imperative for app developers and managers to strengthen the levels of HA to achieve the highest EA, ultimately affecting the subsequent levels of BI. In other words, the users would hold a more positive attitude towards the histogram-based mobile information and increase their intention to purchase e-scooters if the e-scooter app could provide significant effectiveness, supporting users' social processes, automatic response to receive the environmental information, and awareness of environmental protection.

5. CONCLUSION

The proposed app service offers e-scooter riders information on the reduced amounts of air pollution source emissions by replacing scooters with e-scooters, thus establishing their cognitive connection between the e-scooter products and the air quality. The contribution of this research is that the model constructs of HA and EA are useful predictors of the behavioural intention to use the app service. The results of this study indicate that providing different mobile information contents on the same information spindle may not have a significant difference in the impact on the user acceptance and intention and may trigger different constructs and intensities of influence on user acceptance and intention. In particular, under the condition of providing text-based carbon information on an app, the results provided strong evidence indicating that EA is the dominant construct in shaping customers' decisions to adopt e-scooter products. In other words, providing information on the app regarding the reduced carbon source emissions by replacing conventional scooters with e-scooters

to customers may increase their awareness of environmental protection and continuous intentions for the app usage, thereby positively affecting their subsequent PI for e-scooters. In contrast, under the condition of providing histogram-based greenhouse gas information, the PE and BI have been identified as the dominant constructs in affecting the PI for e-scooters. In other words, providing information on the app regarding the reduced $PM_{2.5}$, PM_{10}, CO_2, CO, NO_X, and TSP source emissions by replacing conventional scooters with e-scooters to customers may strengthen their perception of usefulness for the app and continuous intentions for the app usage, thereby positively affecting the subsequent PI for e-scooters. Moreover, the results also verified that smartphone app services are an influential medium and may represent an important part of marketing strategies in the E2W industries. The app designers and managers of such services can consider the abovementioned recommendations when implementing new versions of the app service design for maximising the benefits of mobile information. Finally, this study focused on young adults using the e-scooter app service for the first time. In our future work, this investigation will be extended to long-term user experiences and older adults to understand their needs and the difference in BI and PI needs between long-term and novice users. Future studies should be aimed at establishing the practicality of the results for app service design and promotion purposes of E2W products.

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探討電動機車可削減空氣污染排放量之行動資訊對使用者行為影響

摘要

本研究提出以行動應用軟體服務為平台，呈現騎乘電動機車以取代燃油機車所削減的空氣污染源排放量之資訊內容，以提高用戶對空氣品質的重視、以及電動二輪車產品的購買意願。為探討用戶接受行動資訊服務之影響因素，本研究採用延伸整合型科技接受模式(UTAUT2)為基礎，並加入一個解釋變量(環境認知)來增強模式，進行重複量數設計實驗及問卷調查。實驗設計用於評估二種不同的資訊內容：一為碳排放量的文字訊息；另一種為呈現6種空氣污染源排放量的直方圖式訊息。研究結果顯示，習慣和環境認知是使用者接受行動資訊服務(行為意圖)的重要預測指標。此外，不同的行動資訊內容對於使用者接受度及行為意圖並無顯著影響；然而，於電動機車的購買意圖卻呈現顯著差異。表示，不同的空氣污染削減量資訊設計，將觸發不同的影響因子及其影響強度。最後，基於研究結果提出相關行動資訊服務設計之建議、以及提供未來創新服務設計之參考依據。

關鍵詞
綠能車輛；空氣污染；使用者經驗；互動；行為意圖。

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