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The Acceptance Analysis on the Use of Beam E-Scooter Sharing Applications in the Public Campus Environment with a Modification of the UTAUT2 Model

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***Abstract*—Micro-mobility, particularly e-scooter services, is becoming increasingly popular on campus as an environmentally friendly and efficient transportation solution. The Beam Mobility application, as a provider of e-scooter services, enables users to rent vehicles through a mobile app. As urban campuses seek sustainable and cost-effective mobility solutions, understanding user behavior toward e-scooter adoption becomes essential. This study aims to identify the factors influencing behavioral intention and actual use of the Beam application in a university environment using the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model, with the addition of one external variable, Information Quality. The research involves one hundred respondents from the campus environment, selected using purposive sampling. Data were analyzed using Partial Least Squares-Structural Equation Modeling (PLS-SEM) to validate the research model using SmartPLS3. The analysis results show that performance expectancy, social influence, hedonic motivation, and price value significantly impact the intention to use the beam application. In contrast, effort expectancy, facilitating conditions, and information quality do not have a significant effect. These findings suggest that functional benefits, peer influence, and Hedonic Motivation are more dominant in shaping user adoption than ease of use or external support systems. This investigation grants insight to the developers of Beam Mobility to enhance the Hedonic Motivation provided to users and improve the emotional experience felt by users while using the application.**

***Keywords*—Micro-mobility; beam mobility application; UTAUT2; technology acceptance; e-scooter; PLS-SEM.**

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I. INTRODUCTION

The use of electric bicycles is gradually being implemented in public campus environments in various countries [1], including Indonesia. This is done because electric bicycles are attracting global attention towards more environmentally friendly mobility trends [1], [2], [3]. In this context, electric bicycles are not only a form of transportation, but also a symbol of efforts to reduce gas emissions and promote a greener lifestyle [4].

With increasing sustainability awareness, Beam Mobility will come to Indonesia by the end of 2022 as the largest micro-mobility service in Asia Pacific, especially in urban areas, providing access to electric bicycles equipped with mobile applications to support effective and efficient mobility. By early 2024, the user satisfaction rate will reach 99%, with an average of 0.55% complaints per month, including malfunctioning units (20.5%), trip termination confusion (18%), and requests for additional information (16%) [5] .

In 2023, several public campuses in Indonesia, including Universitas Brawijaya, Universitas Padjadjaran, Universitas Indonesia, and Institut Pertanian Bogor, collaborated with Beam Mobility Indonesia to introduce electric bicycles as part of the green public campus initiative. These electric bicycles are equipped with advanced technology connected to the Beam app, which serves to register and rent bicycles easily through a smartphone. The app helps users find the nearest parking spot, has a detailed guide, and offers a sharing feature that can be used to rent more than one bike simultaneously.

According to the researcher's initial observation interview, ten beam users admitted using this application because of their curiosity to try new technology. This shows that an individual's interest in the system can influence their interaction with the application. User satisfaction with the system increases as interest increases [6], [7]. Research by [8] perceived responsiveness reflects the frequency and speed of response to questions and requests from users [9]. Therefore, the level of acceptance of technology will increase if responsiveness is improved.

Further research should be conducted to identify the key factors influencing technology adoption within the Beam application. On the other hand, it is hoped that the company can formulate an effective strategy to ensure that the product can be well received by users, not only in the urban environment but also in the rural environment, which has quite different criteria for needs, goals, distance, and others [4], [10], [11], [12]

Several researchers have developed various models scientifically to determine the level of technology acceptance, such as the Technology Acceptance Model (TAM) by Davis in 1985, the Unified Theory of Acceptance and Use of Technology (UTAUT) [13], followed by its latest version, UTAUT2. [14]. The study investigates the factors influencing the acceptance of Beam application technology, utilizing the UTAUT2 model as the conceptual framework. The UTAUT2 model is more comprehensive than the TAM and UTAUT models. This is since the UTAUT2 model integrates elements from several preceding technology acceptance models[15], [16]

A. Extension of Unified Theory of Acceptance and Use of Technology (UTAUT2)

The UTAUT2 model is a remake of the previous UTAUT model, developed to provide a more thorough insight into the determinants that affect users' decisions in adopting new technologies [13]. The UTAUT2 model is beneficial because it recognizes the significant role that personal satisfaction and habits play in technological adoption in the user sphere. The additional constructs allow researchers and practitioners to predict better and understand how users adopt and use technology, thus providing a more comprehensive framework than its predecessors and other technology adoption models such as TAM, UTAUT, etc. The modification resulted in the UTAUT2 model. This modification resulted in the UTAUT2 model, which was shown to increase the variance of Behavioral Intention to 74% (from 56%) and technology use to 52%, which was previously 40% [14]. In addition, 74% of the variance in user adoption [17]. This is a testament to its effectiveness in studying technology adoption [14].

The UTAUT2 model has been refined by removing the habit variable and demographic moderators (age, gender, and experience) to better align with the research context. This study focuses on adopting the Beam application within a public university environment, emphasizing technological and environmental factors rather than demographic differences or habitual behaviors. Prior research [14] has eliminated variables such as habit and demographic moderators, which can simplify the model without reducing its validity in early-stage technology adoption studies or homogeneous populations.

The Habit variable in UTAUT2 represents the automatic use of technology formed through prolonged experience [18] [19]. However, in the early adoption stage of the Beam application, users have not had sufficient exposure to develop habitual usage patterns [20]. Habit formation requires repeated interactions over time [21], demonstrate that habit only becomes influential after prolonged use in mHealth applications [22]. Given the novelty of the Beam application, habit is not yet a determining factor in its continued usage, justifying its exclusion from this study.

In this study, age, gender, and experience variables were also excluded because the target population of this study is primarily students who are relatively homogeneous in terms of demographics in a public campus environment. These variables act as moderators in the UTAUT2 model, potentially influencing the connection between the core constructs and behavioral intentions [14]. However, in the context of this study, which generally has a similar age range, experience, and educational background, the role of these moderators is less significant [23]. Thus, this study focuses solely on the core constructs of UTAUT2 without incorporating habit and demographic moderators (Fig. 1).

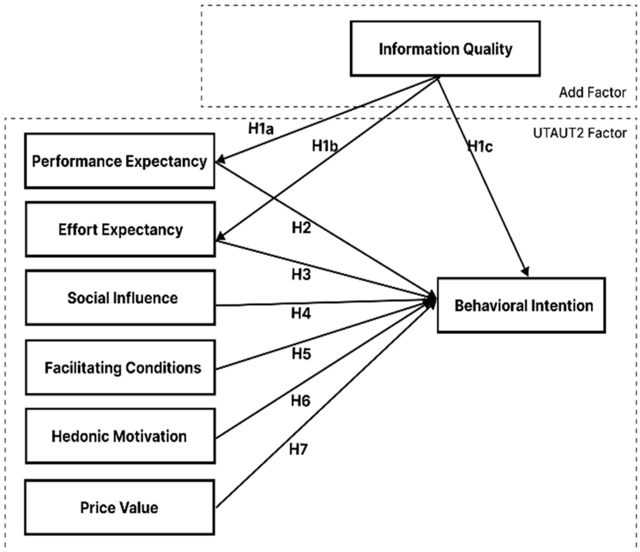

Fig. 1 Research Conceptual

B. Information Quality for Behavioral Intention to Use Technology Beam

Information Quality is one of the critical factors that determine the success of a technology [24]. Information quality refers to the completeness, relevance, accuracy, and clarity of the information presented by the system to its users [25]. Accurate and relevant information increases user confidence in technology and plays a vital role in reducing uncertainty [26], [27]. Information Quality factors also have a significant relationship to Performance Expectancy in e-learning users [28], [29]. Furthermore, information quality was found to play a key role in improving the performance expectations and workload expectations of mobile application users [24], [30].

However, in the context of other variables such as Facilitating Conditions, Social Influence, Hedonic Motivation, Facilitating Conditions, and Price Value, the effect of Information quality is not significant because different social, technical, or emotional factors more influence these variables [13], [31]. Therefore, this research model only connects Information Quality with theoretically and empirically relevant variables to explain user behavior intention.

- H1a: Information Quality significantly influences Effort Expectancy in using the Beam application.

- H1b: Information Quality significantly impacts Effort Expectancy in using the Beam application.
- H1c: Information Quality significantly impacts Behavioral Intention in the use of the Bea application.

C. Performance Expectancy for Behavioral Intention to Use Technology Beam

Performance Expectancy denotes the degree to which individuals feel that utilizing technology provides substantial advantages in carrying out particular tasks [14]. When users believe that technology will provide improved performance, it indicates high performance expectations. The more intense this belief is, the more likely the user is to engage with the technology [24].

- H2: Performance expectancy significantly influences behavioral intention when using the beam application.

D. Effort Expectancy for Behavioral Intention to Use Technology Beam

Effort Expectancy refers to the extent to which they perceive the technology they use as easy to learn and operate [14]. This includes several aspects, such as the time required to learn to use the application, how intuitive the features are, and the ease of access to the services provided [32]. The stronger the user's perception of the application's ease of use, the higher the likelihood of their intention to adopt it.

- H3: Effort Expectancy significantly influences behavioral intention when using the Beam application.

E. Social Influence for Behavioral Intention to Use Technology Beam

The level of influence exerted by friends or family on a person's decision to adopt a particular technology is considered social influence [13]. Previous literature has extensively highlighted social factors as key determinants that influence an individual's decision to adopt a new system [33]. If individuals believe that people in their environment encourage the adoption of a specific technology, it may increase their chances or intention to use it [14].

- H4: Social influence significantly influences behavioral intention when using the Beam application.

F. Facilitating Conditions for Behavioral Intention to Use Technology Beam

Facilitating Conditions involve the availability of necessary infrastructure and resources that enable the effective use of technology [13]. Research shows that the better the supporting conditions, the greater the chance that technology will be adopted [14], [32]

- H5: Facilitating conditions significantly influence behavioral intention when using the beam application.

G. Hedonic Motivation for Behavioral Intention to Use Technology Beam

Hedonic Motivation variable refers to the emotional satisfaction that users get from interacting with technology [14]. It includes aspects such as the pleasure gained while using the app, the convenience of accessing the service, and other positive experiences that increase user satisfaction. Research indicates that higher levels of perceived emotional satisfaction increase the likelihood of continued technology usage [34].

- H6 Hedonic Motivation significantly influences behavioral intention when using the beam application.

H. Price Value for Behavioral Intention to Use Technology Beam

Price Value represents the user's evaluation of the trade-off between the benefits received and the costs incurred when using a technology [14]. In this study, Price Value is defined as public campus users' assessment of the cost of renting an electric bicycle through the Beam Mobility application compared to the benefits obtained, such as ease of transportation, time savings, and other positive experiences. Previous studies indicate that individuals are more likely to embrace technology when they perceive the advantages to be greater than or at least on par with the associated costs [34], [35]

- H7 Price value significantly influences behavioral intention when using the Beam application.

II. Materials and Methods

A. Sample and Data Collection

Quantitative methods to test theories objectively by analyzing the relationship between variables and collecting structured data from Beam application users. The population consists of all Beam users in a public campus environment who have access to Beam services, so that the sample taken accurately reflects the characteristics of the population. The research sample consisted of 100 participants, with a minimum of 80 respondents recommended by Cohen (1992) to achieve 80% statistical power at the 5% significance level with seven latent variable paths (Fig.1), to ensure optimal statistical analysis [36].

Data collected was gathered through an online survey utilizing a questionnaire shared with participants via the Google Forms platform. Before the main survey, a pilot study involving 30 respondents was carried out to assess the questionnaire, identify any weaknesses, and make necessary revisions [37], and evaluate the extent to which the research instrument can accurately represent the concept under study [38]. Initial testing was also carried out, using Expert judgment involving two experts with experience to evaluate the research instruments [39]. After the pilot study and Expert judgment were declared valid and reliable, the main research was conducted with a larger sample to answer the hypothesis more thoroughly.

The samples were selected using a non-probability sampling method, with purposive sampling as a specific approach. This approach was chosen because the researcher needed respondents who had specific characteristics that suited the study's needs. Purposive sampling helps researchers selectively choose individuals with relevant and significant research characteristics. The research subjects consisted of Beam app users in a public campus environment who had used the app at least once.

TABLE I
RESEARCH QUESTION

Construct	Item
Information Quality (IQ)	The Beam app gives me the latest information The Beam app provides easy-to-understand information The Beam app gives me all the information I need. The information provided by the Beam app is displayed on the screen. The information provided by the Beam app is accurate.
Performance Expectancy (PE)	I find using the Beam a valuable app in my life in a public campus environment. The Beam app allows me to locate Beam bikes quickly. The Beam app has improved the efficiency of my activities.
Effort Expectancy (EE)	I found that learning how to use the Beam app was easy for me. I can easily use the Beam App. I realized that the instructional information on how to use the Beam app was easily accessible to me.
Social Influence (SI)	People around me influenced my behavior by using the Beam app. Important/known people can influence my decision to use the Beam app. My friends recommended that I use the Beam App that they use. I used Beam's service because it has good reviews/reputation.
Facilitating Conditions (FC)	The Beam app runs smoothly on my smartphone. I have sufficient knowledge on how to use the Beam app. I realized that the Beam app help service was available to me. I can ask others for assistance when I run across issues using the Beam app.
Hedonic Motivation (HM)	I feel happy when using the Beam App. I am happy with the discounts provided by the Beam app, whether for special events or promotional campaigns. I like booking Beam bike services through the Beam app
Price Value (PV)	The Beam app provides reasonable rates. The Beam app provides an acceptable price value. I can save money by using the Beam app for transportation. The Beam app is more reasonably priced than similar apps. At current prices, the Beam app provides good value.
Behavioral Intention (BI)	I will continue to use the Beam app service, assuming I have downloaded and owned the app. Should I have access to the Beam app, which I believe would be utilized effectively? I plan to use the Beam app frequently when it becomes available.

B. Demographics of Respondents

Demographics of respondents with a total of 100 within 2 weeks, with the following statistics:

TABLE II
DEMOGRAPHIC STATISTICS (N=100)

Characteristics	N
Gender	
Male	50
Female	50
Domicile Area Campus	
Brawijaya University	73
Universitas Indonesia	15
Padjadjaran University	11
Institut Pertanian Bogor	1
Job	
College Student	95
Private Employee	4
Student	1

The respondents' gender was balanced between men and women, totaling fifty people or 50%. The majority were College Students, with ninety-five people (95%), four (4%) were private employees, and one student. This shows a high dominance of students in this study, which is undoubtedly relevant to the public campus environment as the primary focus.

The distribution of respondents by university of origin shows that the majority came from Brawijaya University 73 respondents (73%), University of Indonesia 15 respondents (15%), Padjadjaran University 11 respondents (11%), and Bogor Agricultural University 1 person (1%). It can be concluded that Brawijaya University is the largest contributor.

C. Data Analysis

The initial phase of this research involved assessing validity through Pearson's product-moment correlation and determining reliability using Cronbach's alpha, with both analyses performed using SPSS 23. The main model was tested using covariance-based structural equation modeling (PLS SEM) through SmartPLS3. PLS-SEM was chosen to be both recursive and path analysis, offering greater flexibility, especially in conditions where data do not meet the assumption of normality [40]. By utilizing the PLS-SEM method, researchers can gain deep insight into the complex relationships between variables and verify hypotheses more effectively, making it a handy tool in quantitative research [41]

Confirmatory factor analysis (CFA) was conducted to evaluate the measurement model, ensuring its reliability and validity, and the validity of the observed data. After confirming the measurement model, we analyzed the structural model to assess the relationships among the variables in the proposed framework, providing empirical support for the statistical findings.

Assume testing was performed before conducting the principal analysis to minimize potential bias, including sample size assessment, data normality, and outlier removal. To ensure representativeness of the total number of respondents obtained, N=115, a minimum sample size requirement of 100 data points was met. After removing 15 irregularities, the 100 data points were confirmed to follow univariate and multivariate normal distributions. Outliers were identified and removed by analyzing the Mahalanobis D-Squared value, focusing on the data points furthest from the center of the distribution.

III. RESULTS AND DISCUSSION

A. Measurement Model Analysis

The measurement model was assessed to examine the relationships between indicators and variables. In this study, validity was tested by measuring convergent validity and discriminant validity. The criteria for convergent validity include that the outer loading value must exceed 0.7 [27]. The data presented in Table III indicates that the statement indicators have met the criteria with a loading value higher than 0.7.

TABLE III
CONVERGENT VALIDITY

Indicator	Loading Factor	AVE	CR
PE1	0.868		
5	0.737	0.697	0.873
PE3	0.891		
EE1	0.850		
EE2	0.899	0.734	0.892
EE3	0.820		
SI1	0.765		
SI2	0.834	0.593	0.853
SI3	0.754		
SI4	0.724		
FC2	0.755		
FC3	0.830	0.644	0.844
FC4	0.821		
HM1	0.847		
HM2	0.801	0.688	0.869
HM3	0.839		
PV2	0.802		
PV3	0.858	0.734	0.917
PV4	0.887		
PV5	0.877		
IQ1	0.847		
IQ2	0.879	0.743	0.896
IQ3	0.859		
BI1	0.849		
BI2	0.818	0.734	0.892
BI3	0.901		

The reliability test on the outer model is essential in evaluating the quality and consistency of the constructs used. Several statistical measures are used to assess these two aspects, including Cronbach's Alpha, Composite reliability, rho_A, and Average Variance Extracted (AVE). Variables are considered reliable when the Composite Reliability and Cronbach's alpha values exceed 0.7 [27].

Based on the preliminary results, the value after removing indicators with the smallest values of FC1, PV2, IQ4, and IQ5 has increased the outer loading value. This shows that removing indicators that do not meet the criteria can increase the reliability of the measured construct. Therefore, all remaining indicators have met the outer loading value criteria of 0.708 or higher. These findings suggest that the indicators are reliable in accurately measuring their respective constructs. The results of the reliability test are presented in Table III. The results suggest that the value of all CR latent constructs, Cronbach's alpha, exceeds 0.70, and AVE exceeds 0.50; all research variables meet the reliability criteria.

Discriminant validity was confirmed using the Heterotrait-Monotrait Ratio (HTMT) method, which calculates the average correlation between indicators of different constructs. This method compares the geometric mean of the correlations between indicators measuring the same construct [27], [28], [29]. Table IV shows that all HTMT values are below the maximum limit of 0.90. This confirms that the measurement has adequate discriminant validity, thus supporting the model's suitability for subsequent analysis.

TABLE IV
DISCRIMINANT VALIDITY

	BI	EE	FC	HM	IQ	PE	PV	SI
BI								
EE	0.197							
FC	0.358	0.485						
HM	0.749	0.455	0.486					
IQ	0.578	0.447	0.844	0.741				
PE	0.750	0.203	0.397	0.692	0.596			
PV	0.686	0.201	0.348	0.581	0.488	0.585		
SI	0.571	0.198	0.499	0.615	0.474	0.388	0.328	

The structural model fit analysis also used the Standardized Root Mean Square Residual (SRMR), with the SRMR result for the Estimated Model recorded at 0.099. This value is slightly above the conventional threshold of 0.08, but is still within the looser tolerance range, which is below 0.10 [42]. As such, this model can be considered to have an acceptable fit.

B. Structural Model Test

Path coefficients were tested using SmartPLS3 to assess the structural model. Hypotheses were considered statistically significant at a 5% significance level, requiring a p-value less than 0.05 and a t-value greater than 1.96 [41]. The model's effect size was measured using the squared multiple correlation coefficient (R^2). The R^2 value (BI) was 0.574, with an adjusted R^2 of 0.541, indicating moderate explanatory power; the independent variables in the model explain 57.4% of the variance in BI. In contrast, the R^2 for Effort Expectancy (EE) was 0.139, with an adjusted R^2 of 0.130, and for Performance Expectancy (PE), the R^2 was 0.229, with an adjusted R^2 of 0.221, reflecting weaker explanatory power. This suggests that only 13.9% of the variance in (EE) and 22.9% of the variance in (PE) can be explained by independent variables.

Additionally, hypothesis testing was performed by calculating the estimated path coefficients, t-statistic values, and p-values obtained through the bootstrapping procedure. The bootstrap method applied in this analysis involved 5,000 samples and a significant level of 5%. A hypothesis is considered supported if the t-statistic exceeds 1.96 and the p-value is less than 0.05 [40]. Detailed test results can be seen as follows:

TABLE V
RESULTS PATH COEFFICIENTS

Hypothesis		Path coefficients	T Statistics	P Values	Result
H1a	IQ → PE	0.479	5.369	0,000	**Accepted**
H1b	IQ → EE	0.373	4.327	0,000	**Accepted**
H1c	IQ → BI	0.087	0.689	0,245	Not Accepted
H2	PE → BI	0.283	3.212	0,001	**Accepted**
H3	EE → BI	-0.033	0.436	0,332	Not Accepted
H4	SI → BI	0.210	2.316	0,010	**Accepted**
H5	FC → BI	-0.083	0.811	0,209	Not Accepted
H6	HM → BI	0.194	1.895	0,029	**Accepted**
H7	PV → BI	0.293	4.157	0,000	**Accepted**

As indicated by the path coefficient test results of Table V of the nine hypotheses tested, six were supported (H1a, H1b, H2, H4, H6, and H7), corresponding to (PE, SI, HM, and PV). Meanwhile, three hypotheses (H1c, H3, and H5) relating to EE, FC, and IQ were rejected.

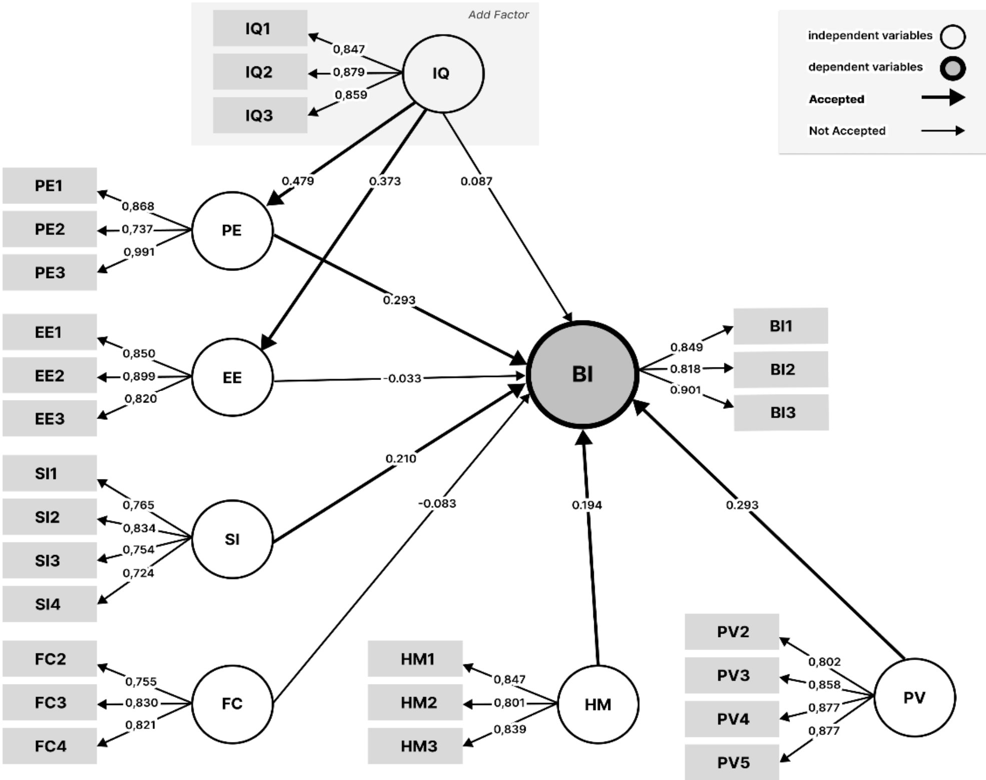

Fig. 2 Results PLS-SEM Hypothesis

1) Effect of Information Quality on Performance Expectancy (H1a)

Hypothesis H1a examines the effect of IQ on the PE of Beam application users. PE refers to the belief that utilizing specific technologies can enhance user's performance outcomes [13]The analysis results show that the IQ provided by the Beam application has a significant effect on PE's performance expectations, indicated with a β = 0.479, t-statistic = 5.369, and p-value = 0.000. This further confirms that the effect is statistically significant, so hypothesis H1a is accepted.

These results align with previous studies indicating that IQ plays a crucial role in shaping users' PE regarding technology [24], [32]. Information quality includes aspects such as accuracy, relevance, completeness, and ease of understanding [26]. Thus, keeping the quality of information high is an essential step towards improving the overall user experience. Developers of the beam app should focus on ensuring that the information provided within the app is consistently accurate, relevant, and easy to comprehend.

2) Effect of Information Quality on Effort Expectancy (H1b)

Hypothesis H1b in this study examines the effect of IQ on user EE in using the Beam application. (EE) refers to the user's perception of the ease of use of a technology. The analysis results show that (IQ) has a significant effect on effort expectancy, with a β = 0.373, t-statistic = 4.327, p-value = 0.000) indicate that hypothesis H1b is accepted, which means that the quality of information provided by the Beam application affects user perceptions regarding the ease of use of the application. This finding, in conjunction with previous research explains the results that high information quality can reduce users' cognitive load and enhance their perceptions of technology's ease of use [24], [32], [43].

3) Effect of Information Quality on Behavioral Intention (H1c)

In information systems, IQ refers to the level of accuracy, relevance, completeness, and ease of understanding of the information provided by technology for its users. Testing was conducted to evaluate whether the quality of the information supplied by the Beam application affects the user's intention of BI to continue using the application in the future. BI is defined as the user's intention or desire to continue using the technology. The analysis results show that IQ has no significant effect on user intention, with a β = 0.087, t-statistic = 0.689, p-value = 0.245. Based on these results, hypothesis H1c is rejected.

The responses from the open-ended question also support this finding, where the quality of information in the Beam app is considered good. Still, this aspect is not the main factor that determines users' decisions to use the app on an ongoing basis. Some users prefer other factors, such as the availability of private transportation or the convenience of walking, especially in the less spacious environment of a public campus. For them, the Beam app is more often used for entertainment purposes or in specific situations. This suggests that while the information provided by the Beam app is useful, other factors such as ease of access to private transportation and environmental conditions influence users' decisions to use the app more.

4) Effect of Performance Expectancy on Behavioral Intention (H2)

Hypothesis H2 examines the effect of PE on BI when using the Beam application. PE is defined as the user's perception that using technology will help users achieve better performance. The analysis results show that PE significantly affects Behavioral Intention with a β = 0.283, t-statistic = 3.212, p-value = 0.001. Thus, hypothesis H2 is accepted, which means that users' perception that the Beam application can improve their performance significantly affects their intention to use this application. This result is consistent with research findings [44] which showed that the PE variable is a strong predictor of users' BI towards technology [13]

The results of the open-ended responses also support these findings. Many users stated that the Beam app helped them improve efficiency and productivity on the public campus. They found it helpful that the app's features helped them find bicycles quickly, saving them time and energy when moving between locations on public campuses. Some users emphasized that the easy access to bicycles displayed on an accurate and real-time map was one of the reasons they felt the app could support their performance in their daily activities, especially in situations that require quick mobilization.

5) Effect of Effort Expectancy on Behavioral Intention (H3)

Hypothesis H3 examines the effect of EE on BI when using the Beam application. EE is defined as the user's perception of technology's ease of use. The analysis results show that Effort Expectancy has no significant effect on Behavioral Intention, with a β = -0.033, t-statistic = 0.436, p-value = 0.332. Hypothesis H3 is rejected. This indicates that users' perceptions of the Beam app's ease of use are not strong enough to influence their intention to continue using it.

6) The Effect of Social Influence on Behavioral Intention (H4)

Hypothesis H4 examines the effect of SI on BI when using the Beam application. Social Influence is the degree to which individuals feel social pressure or encouragement from the social environment to use certain technologies. The analysis results show that the SI factor significantly affects BI, with β = 0.210, t-statistic = 2.316, p-value = 0.010. Therefore, hypothesis H4 is accepted, which indicates that encouragement and recommendations from users' social environment, such as friends, family, or colleagues, significantly influence their intention to use the Beam app.

7) The Effect of Facilitating Conditions on Behavioral Intention (H5)

Hypothesis H5 examines the effect of FC on BI when using the Beam application. FC is defined as the user's perception of the available resources and support needed to use the technology. The results of the analysis show that FC does not have a significant effect on (BI), with β = -0.083, t-statistic = 0.811, p-value = 0.209, so that hypothesis H5 is rejected. This shows that although resources and support for using the Beam application are available, this is not enough to influence users' desire to continue using the application. This result is in line with research [44]

8) The Effect of Hedonic Motivation on Behavioral Intention (H6)

Hypothesis H6 examines the effect of (HM) on (BI) in using the Beam application. Hedonic Motivation refers to the satisfaction gained from using technology. Based on the analysis results, it was found that HM has a significant influence on (BI), with a β = 0.194, t-statistic = 1.895, p-value = 0.029. Therefore, hypothesis H6 is accepted, indicating that emotional satisfaction and pleasure derived from using the Beam app significantly influence users' intention to use it.

The concept of hedonic motivation is closely related to gamification, which involves designing services and systems to create experiences similar to those found in games [45]. hedonic values, gamification enhances user motivation and engagement across various domains, such as marketing, education, and healthcare [46]. Task or quest-based affordances, often linked to achievements in gamification, enhance user motivation by providing rewarding challenges, encouraging continuous interaction [45]. These structured tasks allow users to develop new skills and achieve clear goals, reinforcing their sense of competence and satisfaction [47]. While the Beam application does not explicitly incorporate gamification, its ability to provide emotional satisfaction and a sense of accomplishment aligns with the motivational effects observed in gamified systems, ultimately increasing user intention to continue using the app.

9) Effect of Price Value on Behavioral Intention (H7)

Hypothesis H7 examines the effect of PV on BI when using the Beam application. PV is defined as the user's perception of the balance between the user's benefits and the costs incurred to use the technology. The analysis results show that PV significantly affects BI with a β of 0.293, t-statistic = 4.157, p-value of 0.000. Therefore, hypothesis H7 is accepted, indicating that users' perception of the balance between costs and benefits of using the Beam application significantly influences their intention to use it. These findings are relevant to prior research, which underscores the importance of price value in the adoption of technology [14]

IV. Conclusion

In conclusion, this study shows that PE, SI, HM, and PV factors significantly influence the intention to use the Beam Mobility application. However, EE, FC, and IQ do not provide a strong enough influence to encourage continued use. These findings suggest that focusing on emotional experiences and user-price value is more important in increasing user engagement of the Beam app. These findings allow Beam Mobility developers to develop more effective strategies.

Some of these solutions are intended to increase user satisfaction and loyalty towards Beam Mobility. App developers who have implemented these strategies can consider some suggestions, such as adjusting the level of gamification challenges, offering reward coupons or discounts, and ensuring the technical reliability of the app to improve the overall user experience.

The limitations of this study reveal opportunities for future research. Given the limited sample size, future research needs to expand the sample to obtain more representative results. In addition, future research also needs to analyze the physical aspects of the Beam electric bike, including safety, comfort, and technical performance. Finally, researchers may consider incorporating new variables, such as Gamification, System Quality, and Personalization, to further explore the factors that can increase user engagement and loyalty in micro-mobility.

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