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Jurnal Pensil Pendidikan Teknik Sipil

Journal homepage: http://journal.unj.ac.id/unj/index.php/jpensil/index

ANALYZING THE DETERMINANTS OF BEAM MICRO-MOBILITY ADOPTION: A TECHNOLOGY ACCEPTANCE MODEL (TAM) APPROACH (A CASE STUDY OF BINTARO JAYA, INDONESIA)

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P-ISSN: 2301-8437
E-ISSN: 2623-1085

ARTICLE HISTORY
Accepted:
26 Maret 2025
Revision:
27 Mei 2025
Published:
30 Mei 2025

ARTICLE DOI:
10.21009/jpensil.v14i2.54378

Abstract

This study analyzes the acceptance of the Beam micro-mobility service in the Bintaro Jaya area. With increasing urbanization and the growing demand for eco-friendly transportation, Beam presents a sustainable mobility solution. The study employs the Technology Acceptance Model (TAM) framework, incorporating an additional environmental awareness variable to assess the factors influencing user acceptance. Primary data was collected through Google Forms questionnaires and field observations, while secondary data was gathered from relevant literature. The analysis was conducted using Structural Equation Modeling (SEM) based on Partial Least Squares (PLS), implemented in SmartPLS 4 software. The findings reveal that young and active demographics dominate the user base, with fairly regular usage patterns for various purposes, particularly recreation. The study also identifies several implementation challenges, including safety concerns and user discipline issues. Key results indicate that ease of use, perceived benefits, and environmental awareness significantly influence behavioral intention to adopt Beam's micro-mobility service. Important findings reveal that perceived benefits, ease of use and environmental awareness play a significant role in shaping the intention to use Beam's micro-mobility service. Furthermore, behavioral intention was found to have a strong correlation with actual usage of the service. These insights are expected to assist Beam managers and policymakers in enhancing the adoption of more efficient and sustainable micro-mobility solutions.

Keywords: Micro-Mobility, Technology Acceptance Model, Bintaro Jaya

Introduction

The transportation industry is a significant contributor to air emissions, including both greenhouse gases and air pollutants (Alhindawi et al., 2020; Schnell et al., 2019). Its substantial impact on climate change highlights the pressing need to implement environmentally sustainable technologies. To mitigate this impact, (Rocha et al., 2023; Santos et al., 2023) cities must transition to greener urban transportation systems. Electric vehicles offer a clean and efficient solution to reduce pollution and carbon emissions while improving air quality and urban environments. Recent studies have shown that the transition to greener urban transportation systems involves developing efficient public transit networks (Hrelja et al., 2020; Shanmukhappa et al., 2019), promoting active transportation modes like cycling and walking (Ermagun & Samimi, 2015; Ferrari et al., 2022; Glazener & Khreis, 2019) and incentivizing the use of electric and low-emission vehicles (Staffell et al., 2019; Urrutia-Mosquera & Fábrega, 2021).

Micro-mobility offers a cutting-edge solution for urban transportation, specifically tailored for short trips and addressing the challenges of first- and last-mile connectivity in city transit systems. This approach opens up new possibilities for urban transport strategies, potentially improving the quality of life for all city dwellers (Alattar et al., 2021; Dwivedi et al., 2022). Solutions in micro-mobility, such as electric scooters, bike-sharing programs, and other small, lightweight vehicles, present flexible and eco-friendly alternatives to traditional urban transport methods (Oeschger et al., 2020). Beam micro-mobility, which relies on electric scooters, provides an environmentally conscious transportation option, allowing users to rent scooters for short urban trips with ease (Ignaccolo et al., 2022; Orozco-Fontalvo et al., 2023). The benefits of the beam include its accessibility, environmental sustainability (Fazio et al., 2021; Felipe-Falgas et al., 2022) and its role in reducing carbon emissions on a smaller scale (Schelte et al., 2021).

While micro-mobility solutions like beam offer significant benefits, they continue to face implementation challenges, including safety risks (Yang et al., 2020), vehicle design limitations, user non-compliance (Gössling, 2020; Yang et al., 2020) and affordability concerns. These operational hurdles reflect the broader systemic barriers to sustainable transportation adoption identified by (Gabriel, 2016), which encompass financial constraints, technological costs, skilled labor shortages, infrastructure gaps, market concentration, and inadequate policy frameworks. Current research emphasizes that addressing these multidimensional challenges requires a dual approach, the first developing strong regulatory systems with effective interagency coordination to overcome structural barriers (Abduljabbar et al., 2019; Gössling, 2020). Second, implementing comprehensive public education initiatives to enhance user behavior and social acceptance. This combined strategy could potentially resolve existing limitations while maximizing micro-mobility's sustainable transportation potential.

Similar to the barriers faced in the renewable energy landscape (Obuseh et al., 2025; Painuly & Wohlgemuth, 2021), micro-mobility solutions must navigate intricate governance challenges that impede their proliferation (Alam et al., 2024). Addressing these regulatory obstacles is essential to encourage investment and societal adoption, thus unlocking the full potential of micro-mobility solutions. Utilizing TAM method (Davis et al., 1989), researchers can identify factors influencing individuals' acceptance of this micro-mobility mode as an environmentally friendly urban transportation option.

Numerous studies have identified factors that impact the acceptance of urban mobility technologies by users, with a particular emphasis on perceived ease of use and perceived usefulness, which are central to the TAM framework (Jing et al., 2020). Recent studies highlight the interdependence between user experience and urban infrastructure in shaping the adoption of urban mobility solutions (Keszey, 2020; Schuchardt et al., 2021). A multidimensional perspective is essential for applying TAM effectively in this context, enabling research to address the evolving challenges of urban environments (Nikitas et al., 2020). Including environment awareness in TAM model for studying Beam micro-mobility adoption in Bintaro Jaya is relevant because it shows the user's approach towards sustainability. Environmentally concerned individuals may perceive Beam as an effective and environmentally conscious mode of transport (Kopplin et al., 2021a), thereby increasing the likelihood of them using it. Since TAM can be extended with suitable factors, concern for the environment explains why some users are ready to adopt greener transport options. In an urban area like Bintaro Jaya, which has pollution and traffic problems, this factor is important because it captures the motivation from the user side toward cleaner mobility alternatives.

Research Methods

This research explores how Beam's micro-mobility services are received by the general population in Bintaro Jaya, South Tangerang City, particularly among individuals who are familiar with or have previously used this mode of transportation. Data were collected through the random distribution of online questionnaires, promoted via digital flyers placed in various Beam parking zones, including residential areas, recreational spots, and locations integrated with public transportation. This strategy was designed to capture a diverse range of user sociodemographic backgrounds. A total of 100 respondents were successfully gathered. Their characteristics were identified through demographic questions in the questionnaire, covering age, gender, educational background, occupation, and frequency of Beam usage, to ensure data representativeness in line with the research objectives. The study is based on the Technology Acceptance Model (TAM), which has been expanded by adding an external factor: environmental awareness. This modified TAM framework includes this additional element, is illustrated in Figure 1.

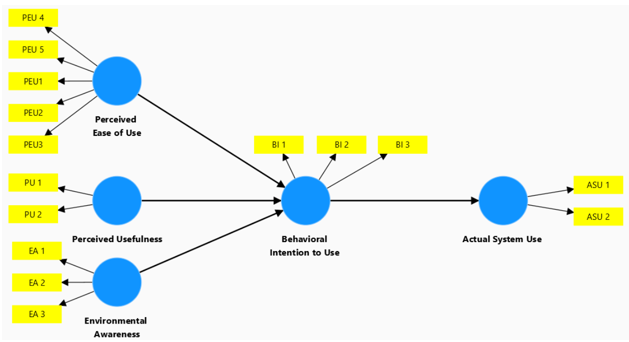

Figure 1. Research model

In this research, variables were assessed using a 5-point Likert scale, offering choices from strongly agree to strongly disagree to gauge participants' perceptions. The data gathered from the questionnaires were analyzed through Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS 4.0, a powerful tool for exploring intricate causal relationships in behavioral studies. The hypotheses were tested at a 5% significance level (*$\alpha = 0.05$*) to evaluate the statistical impact of each predictor variable, such as perceived usefulness, ease of use, and environmental awareness. PLS-SEM was chosen for its capability to manage small-to-moderate sample sizes while concurrently evaluating both measurement and structural models.

Research Results and Discussion

This study utilizes Structural Equation Modeling (SEM) with the Partial Least Squares (PLS) approach, implemented via SmartPLS 4.0, to examine the relationships between latent constructs. The PLS-SEM analysis follows a systematic three-stage process: Outer (Measurement) Model Evaluation, Inner (Structural) Model Assessment and Hypothesis Testing

This study examines five key constructs derived from the extended Technology Acceptance Model (TAM), operationalized through carefully designed Likert-scale item

Table 1. Variables and Statements

Variabel	Code	Statement	
Perceived Ease of Use (PEU)	PEU1	In my opinion, it is very easy to learn how to use the Beam shared e-scooter service	(Fred D. Davis, 1989; Pan et al., 2022)
	PEU2	In my opinion, using the Beam app is easy	
	PEU3	In my opinion, renting a Beam is easy	
	PEU4	In my opinion, returning a Beam is easy	
	PEU5	In my opinion, Beam is very easy to ride	
Perceived usefulness (PU)	PU1	I think Beam can improve travel efficiency	(Fred D. Davis, 1989; Pan et al., 2022)
	PU2	In my opinion, Beam is very useful for daily commuting	
Environmental Awareness (EA)	EA1	The Beam service contributes favorably to urban transport	(Kopplin et al., 2021b; Pereira et al., 2022)
	EA2	I believe that Beam helps protect the environment	
	EA3	I feel that using Beam aligns with the environmental issues around me	
Behavioral Intention to Use (BIU)	BI1	If I have access to the Beam service nearby, I will use it	(Kopplin et al., 2021b; Pereira et al., 2022)
	BI2	I'd definitely recommend Beam to my friends and family	
	BI3	I intend to use the Beam service to support my daily commuting activities	
Actual System Use (ASU)	ASU1	I use Beam as a recreational means	(Pimentel & Lowry, 2020; Şengül & Mostofi, 2021)
	ASU2	I feel satisfied using Beam	

Outer Model Analysis

The outer model analysis, or measurement model testing, is used to understand the relationship between variables and their indicators (Fatihanisya & Purnamasari, 2021). Several steps are involved in conducting the outer model test, including Convergent Validity, Discriminant Validity, Average Variance Extracted (AVE), and reliability testing.

1. Convergent Validity

Convergent validity is assessed by examining the loading factor of each indicator on its associated construct, with validity considered to be established when the outer loading values is greater than 0.7 (Hair et al., 2006). This process aims to enhance the quality and reliability of the analyzed data.

Table 2. Outer Loading

Variable	Item	*Outer Loading*	Description
PEU	PEU1	0.806	Valid
	PEU2	0.725	Valid
	PEU3	0.761	Valid
	PEU4	0.823	Valid
	PEU5	0.743	Valid

Variable	Item	*Outer Loading*	Description
PU	PU1	0.912	Valid
	PU2	0.927	Valid
EA	EA1	0.854	Valid
	EA2	0.803	Valid
	EA3	0.869	Valid
BI	BI1	0.798	Valid
	BI2	0.857	Valid
	BI3	0.822	Valid
ASU	ASU1	0.754	Valid
	ASU2	0.971	Valid

The SmartPLS calculation results presented in the table above demonstrate that all measurement items across the variables exhibit loading factor values exceeding 0.7. This confirms the validity of the constructs in this study. Furthermore, the results indicate that respondents interpreted each independent variable item as intended by the researchers, ensuring consistent and accurate data interpretation.

2. Discriminant Validity

Discriminant validity testing is conducted to ensure a clear distinction between latent variables. The model is considered valid if the HTMT value is less than 0.90 and the cross-loading values exceed 0.70. The results of the discriminant validity test are presented in the table below:

Table 3. Heterotrait-Monotrait Ratio (HTMT) – Matrix

	EA	BI	ASU	PU	PEU
EA					
BI	0.667				
ASU	0.504	0.312			
PU	0.634	0.665	0.335		
PEU	0.452	0.253	0.625	0.558	

The results of the discriminant validity test show that all HTMT values are below 0.90, indicating that the model satisfies the criteria for discriminant validity.

3. Average Variance Extracted (AVE)

The validity of the construct was assessed using Average Variance Extracted (AVE), where an AVE value above 0.5 signifies adequate convergent validity. The calculated AVE scores, summarized in Table 4, confirm the robustness of the measurement model:

Table 4. Average Variance Extracted

Variable	*Average Variance Extracted* (AVE)	Description
ASU	0.756	Valid
BI	0.682	Valid
EA	0.709	Valid
PEU	0.597	Valid
PU	0.846	Valid

Based on Table 4, all AVE values are greater than 0.50, indicating that the data demonstrate adequate convergent validity.

4. Reliability Test

Composite Reliability (CR) is utilized to assess the internal consistency of a group of indicators or latent constructs in a research study. A construct is considered reliable if its CR value exceeds 0.70. In this study, the Composite Reliability values for all variables are presented as follows:

Table 5. Composite Reliability

Variable	***Composite reliability* (rho_a)**	***Composite reliability* (rho_c)**	Description
ASU	1.315	0.859	Valid
BI	0.796	0.865	Valid
EA	0.828	0.880	Valid
PEU	1.002	0.881	Valid
PU	0.822	0.917	Valid

Based on Table 5, the Composite Reliability values for each variable exceed 0.70, indicating that the study meets the required standards for internal consistency. Additionally, reliability testing was conducted using Cronbach's Alpha, with all constructs demonstrating values above the 0.70 threshold. These results confirm that the indicators possess an adequate level of internal consistency in measuring their respective constructs.

Table 6. *Cronbach's Alpha*

Variable	***Cronbach's alpha***	Description
ASU	0.731	Valid
BI	0.771	Valid
EA	0.799	Valid
PEU	0.854	Valid
PU	0.818	Valid

The Cronbach's Alpha values presented in Table 6 indicate that the constructs of Perceived Usefulness (PU), Perceived Ease of Use (PEU), Behavioral Intention to Use (BI), Actual System Use (ASU), and Environmental Awareness (EA) are reliable, as all values exceed the 0.70 threshold. Consequently, it can be concluded that all variable indicators used in this study exhibit strong reliability and can be trusted. This suggests that respondents' answers are both valid and reliable within the context of this research.

Inner Model Analysis

The purpose of testing the structural or inner model is to evaluate and forecast the causal connections among the variables outlined in the research. This process is conducted using the bootstrapping technique through the SmartPLS software. The following are the calculation steps for the inner model test.

1. Coefficient of Determination (R^2)

To assess the extent to which exogenous variables influence endogenous variables, the R Square value is utilized. According to established guidelines, R Square values are interpreted as follows: 0.67 indicates a strong effect, 0.33 a moderate effect, and 0.19 a weak effect (Hair et al., 2011; Henseler et al., 2009). The R Square calculations are as follows:

Tabel 7. The result of *R Square*

	R-square	***R-square adjusted***	**Indication**
ASU	0.086	0.077	weak
BI	0.388	0.369	Moderate

Based on the test results shown in Table 7, the R^2 value for the Behavioral Intention to Use variable is 0.369. This indicates that 36.9% of the variation in Behavioral Intention to Use can be explained by the variables Perceived Usefulness, Perceived Ease of Use, and Environmental Awareness, with a moderate prediction level. Furthermore, the R^2 value for the Actual System Use variable is 0.077, meaning that 7.7% of the variation in Actual System Use can be explained by the Behavioral Intention to Use variable, with a weak prediction level.

2. Effect Size (F^2)

The F Square test is conducted to determine whether the influence of exogenous variables on endogenous variables is categorized as small (0.02), medium (0.15), or large (0.35).

Table 8. *F Square Result*

	ASU	**BI**	**EA**	**PEU**	**PU**
ASU					
BI	0.094				
EA		0.171			
PEU		0.007			
PU		0.144			

Based on Table 8, the F Square values indicate varying levels of influence among the variables. Environmental Awareness (EA) demonstrates a moderate influence on Behavioral Intention (BI), with a value of 0.171. Behavioral Intention (BI) exerts a small influence on Actual System Use (ASU), reflected by a value of 0.094. Perceived Usefulness (PU) also shows a moderate influence on Behavioral Intention (BI), with a value of 0.144. In contrast, Perceived Ease of Use (PEU) has a negligible effect on Behavioral Intention (BI), with a low significance value of 0.007.

3. Relevance Prediction Test Result (Q^2)

To determine the quality of observation values, a predictive relevance test must be conducted using the blindfolding procedure and checking whether the Q Square value is greater than 0. If Q Square value is greater than 0 indicates that the observation values are good (Candes & Tao, 2007). The Q Square calculation is as follows:

Table 9. *Q Square Result*

	Q^2predict
ASU	0.097
BI	0.319

Table 9 shows that all Q² predictive values for BI and ASU are greater than 0, indicating that the model possesses predictive relevance. To confirm that the proposed PLS model has strong predictive power, the RMSE and MAE values should be lower than those of the linear regression model (LM). The following table presents the comparison:

Table 10. PLS *Predict*

Variable	*Q²predict*	PLS-SEM RMSE	PLS-SEM MAE	LM-RMSE	LM-MAE
ASU 1	0.027	0.912	0.752	0.975	0.772
ASU 2	0.109	0.837	0.713	0.820	0.623
BI 1	0.138	0.855	0.686	0.896	0.708
BI 2	0.282	0.679	0.524	0.713	0.553
BI 3	0.221	0.790	0.578	0.835	0.633

From Table 10, it is shown that one measurement item, ASU 2, has a higher PLS-SEM RMSE and MAE value compared to the LM model. However, most other measurement indicators have lower RMSE and MAE values than the LM model, indicating that the PLS-SEM model in this study can capture complex relationships between variables.

Hypothesis Analysis

After the measurement testing stage meets the required criteria, the next step is hypothesis testing using bootstrapping in SmartPLS version 4. The path coefficient indicates the nature of the relationship, whether positive or negative, and assesses the significance of the influence between one latent variable and another (Crocetta et al., 2021). The purpose of the path coefficient test is to determine whether a hypothesis should be accepted or rejected (Putri et al., 2023).

The results of the data analysis are used to test the hypotheses in this study by considering the T-Statistics and P-Value as the basis for hypothesis testing. At a 5% significance level, a hypothesis is deemed significant if the t-statistic exceeds the t-table value of 1.960 and the p-value is below 0.05. The following are the hypothesis test results obtained in this study:

Table 11. *Path Coefficients Result*

	***Original sample* (O)**	***T statistics***	***P values***	**Indication**
BI -> ASU	0.294	2.279	0.023	Significant
EA -> BI	0.385	3.305	0.001	Significant
PEU -> BI	-0.077	0.805	0.421	Not significant
PU -> BI	0.374	2.942	0.003	Significant

a) **Hypothesis 1 (H_1):** Perceived usefulness significantly influences behavioral intention to use the Beam micro-mobility mode. The analysis yielded an original sample value of 0.374, a t-statistic of 2.942 (> 1.96), and a p-value of 0.003 (< 0.05), indicating statistical significance.
b) **Hypothesis 2 (H_2):** Perceived ease of use does not significantly influence behavioral intention to use the Beam micro-mobility mode. The analysis showed an original sample value of -0.077, a t-statistic of 0.805 (< 1.96), and a p-value of 0.421 (> 0.05), suggesting no significant effect.
c) **Hypothesis 3 (H_3):** Environmental awareness significantly affects behavioral intention to use the Beam micro-mobility mode. The analysis produced an original sample value of 0.385, a t-statistic of 3.305 (> 1.96), and a p-value of 0.001 (< 0.05), confirming significance.

d) **Hypothesis 4 (H_4):** Behavioral intention significantly influences actual usage of the Beam micro-mobility mode. The analysis resulted in an original sample value of 0.294, a t-statistic of 2.279 (> 1.96), and a p-value of 0.023 (< 0.05), indicating a significant effect.

Discussion

Impact of Perceived Ease of Use (PEU) on Perceived Usefulness (PU)

The findings reveal that PEU significantly influences PU, as indicated by a t-value exceeding 1.96 and a p-value below 0.05. This means that when a technology is easier to use, users tend to view it as more beneficial. These results support earlier studies by (Fred D. Davis, 1989) and (Pan et al., 2022), who highlighted that ease of use is a critical factor shaping users' perceptions of a technology's usefulness, particularly among younger demographics.

Effects of PU, PEU, and EA on Behavioral Intention to Use (BI)

Perceived Usefulness, Perceived Ease of Use, and Environmental Awareness all positively and significantly affect users' Behavioral Intention to Use Beam's services. This suggests that users consider the practical advantages, ease of operation, and environmental concerns when deciding to use this transportation mode. These conclusions align with research by (Venkatesh & Morris, 2000) and (Pereira et al., 2022) which emphasize that both personal and external factors are vital in shaping technology adoption intentions.

BIU as a Mediator for Actual System Use (ASU)

Behavioral Intention to Use significantly mediates the relationship between PU, PEU, EA, and Actual System Use. The statistical evidence (t-value = 2.279, p = 0.023) confirms that intention is a strong predictor of actual usage behavior. This finding supports the fundamental TAM theory that intention precedes actual use. However, despite strong intentions, real-world use may be limited by factors such as insufficient safety features, user non-compliance with parking rules, and inadequate infrastructure, which can hinder full adoption.

Contextual Factors Influencing the Findings

The high BIU observed can be attributed to the respondents' profiles, mostly young and active individuals with high mobility needs. Nonetheless, actual usage depends on vehicle conditions, local regulations, and perceptions of safety and comfort. Thus, acceptance of the technology is fluid and heavily reliant on the readiness of the surrounding ecosystem.

Comparison with Previous Research

These findings are consistent with Schaefer et al. (2022) and Roslan et al. (2023), who underscored the importance of sociodemographic characteristics, environmental awareness, and user experience in adopting shared mobility solutions. This study enriches the literature by providing insights specific to the Indonesian context, highlighting unique challenges and opportunities in micro-mobility implementation.

Practical and Theoretical Contributions

From a practical standpoint, the study offers Beam operators actionable recommendations such as improving vehicle safety, expanding official parking areas, and enhancing user education. Academically, it advances the TAM framework by incorporating environmental factors within the context of contemporary micro-transport systems, contributing to a more comprehensive understanding of technology acceptance in this domain.

Theory and Practical Implications

This study reinforces the Technology Acceptance Model (TAM) while emphasizing the growing influence of environmental awareness on mobility adoption. It suggests that perceived usefulness and eco-friendliness are stronger predictors of micro-mobility adoption than perceived ease of use. To enhance user adoption and retention, Beam should focus on marketing strategies that highlight the practical benefits of its micro-mobility services, such as improved travel efficiency and productivity, while also emphasizing its environmental benefits. These factors significantly influence behavioral intention. Given the strong impact of sustainability concerns on user decisions, promoting Beam's role in reducing air pollution can effectively attract environmentally conscious riders. Although perceived ease of use does not directly drive adoption, ensuring a seamless user experience remains essential for customer satisfaction and long-term retention. By focusing on practical value and eco-friendly advantages, Beam can strengthen its appeal and encourage greater usage among its target audience.

Conclusion

This study examined the factors influencing the acceptance of Beam's micro-mobility service using the Technology Acceptance Model (TAM) framework. The findings demonstrate that perceived usefulness and environmental awareness significantly and positively influence users' behavioral intention to adopt the service, which in turn predicts actual usage. Contrary to conventional TAM expectations, perceived ease of use showed no significant effect, suggesting that users prioritize practical and environmental advantages over operational simplicity in micro-mobility contexts. This deviation highlights the unique dynamics of sustainable transportation adoption, where ecological values complement traditional utility-based motivations. The findings of this study offer clear guidance for promoting Beam's micro-mobility service. For marketing teams, emphasizing the service's time efficiency and environmental benefits will effectively increase user adoption. While ease of use wasn't a primary adoption driver, maintaining good usability remains important for customer satisfaction and retention. Urban planners and policymakers should support micro-mobility by highlighting its dual advantages of transportation efficiency and sustainability, while also developing appropriate infrastructure and awareness programs. These practical steps can significantly enhance Beam's market penetration while contributing to more sustainable urban transportation systems.

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