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Research Article

Distinct Pathways of Personality Traits in Technology Acceptance: The Mediating Role of Social Support and User Experience in Rail Public Transport

Hwi-Chie Ho[1*], Amir Tjolleng[1], Harjanto Prabowo[2], Dyah Lestari Widaningrum[1], Bertha Maya Sopha[3]

[1]Industrial Engineering Department, Faculty of Engineering, Bina Nusantara University, Jakarta 11480, Indonesia
[2]Management Department, BINUS Business School - Doctor of Research in Management, Binus Business School, Bina Nusantara University, Jakarta 11480, Indonesia
[3]Department of Mechanical and Industrial Engineering, Universitas Gadjah Mada, Yogyakarta 55281, Indonesia
[*]Corresponding author: hhchie@binus.edu; Tel.: +62-21-534-5830; Fax.: +62-21-530-0244

Abstract: This study applies Conservation of Resources (COR) theory to examine technology acceptance in rail-based public transportation through an integrated structural path model linking the Big Five personality traits, intention to use, social support, user experience, and continuance-oriented technology acceptance. Survey data from 584 commuters in the Jakarta metropolitan area, Indonesia, were analyzed using Structural Equation Modeling (SEM). The proposed model shows good fit and substantial explanatory power (R^2 = 0.58 for user experience, 0.72 for social support, and 0.79 for technology acceptance). The findings indicate that technology acceptance follows multiple entry points rather than a single uniform route: agreeableness, conscientiousness, and neuroticism are associated with intention to use, openness with social support, and extraversion with user experience. Intention to use also plays a dual role by directly influencing and indirectly shaping technology acceptance through social support and user experience. Overall, this study extends conventional linear acceptance models by offering an integrated and context-sensitive explanation of sustained public rail acceptance in an urban collectivist setting. As this study is based on cross-sectional data, future research could further examine these pathways using longitudinal or experimental designs.

Keywords: Personality traits; Rail-Based public transportation; Social support; Technology acceptance; User experience

1. Introduction

Public mass transportation plays a vital role in sustainable urban mobility and the quality of life of citizens. Reliable transport systems can reduce dependence on private vehicles, lower air pollution, and expand accessibility across social groups. Previous studies have shown that public transportation service quality is associated with continued usage intention and broader social, economic, and environmental benefits (Mugion et al., 2018). Adequate transport access has also been linked to life satisfaction and mental health (Doebler, 2025). In the context of electric mobility as a service (eMaaS), electrified and digitally integrated rail systems are increasingly regarded as key components of low-emission urban transport ecosystems (Jnr, 2025; Hassan et al., 2021). This makes rail-based systems, such as mass rapid transit (MRT), light rail transit (LRT), and Kereta Rel Listrik (KRL), strategically important for addressing contemporary urban mobility challenges.

This issue is particularly salient in Indonesia, particularly in the Jakarta metropolitan area, where chronic congestion continues to affect economic efficiency and workforce productivity. In response, the government has introduced various interventions, including traffic restrictions and large-scale investments in MRT and LRT infrastructure (PT MRT Jakarta, 2017). However, the

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outcomes remain mixed. Several studies have suggested that these interventions have not fully produced substantial behavioral change (Widita, 2024; Gaduh et al., 2022), while improvements in worker productivity and urban well-being remain limited (Yudhistira et al., 2025). These conditions highlight that the success of MRT, LRT, and KRL systems should be assessed not only in terms of infrastructure provision but also through user acceptance and actual travel experience. Evidence from other contexts also indicates that ease of use, comfort, and fare transparency are associated with public satisfaction and adoption legitimacy (Guo et al., 2025; Wong et al., 2024).

Although service quality has long been recognized as an important determinant of satisfaction and usage intention in public transportation (Bautista et al., 2025; Watthanaklang et al., 2024), prior research has focused mainly on functional attributes and demographic characteristics, paying less attention to relatively stable psychological characteristics such as personality traits, even though these may shape how individuals evaluate benefits, risks, and everyday travel experiences. While recent studies have begun to acknowledge user heterogeneity in mobility behavior (Kriswardhana et al., 2025; Wang et al., 2024), research linking personality traits to technology acceptance in rail-based public transport remains limited. This gap matters not only theoretically but also practically, because a stronger uptake of digitally enabled public transportation may depend on how different users move through the acceptance process.

The issue is particularly relevant in Indonesia's collectivist social context. In socially embedded environments, judgments and behavioral choices are influenced not only by personal evaluation but also by interpersonal assistance, shared interpretation, and relational validation (Kashima et al., 2025). Technology acceptance frameworks, such as the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), recognize the role of social influence, and prior studies in mobility settings have linked social support, intention, and user evaluations to specific aspects of the acceptance process (Nordhoff and Lehtonen, 2025; Wei et al., 2024). However, these studies largely examine isolated links rather than how such factors operate together within an integrated structural model. This limitation is especially important in digitally enabled rail systems, where acceptance may follow different user-specific pathways rather than a single uniform route. Stronger uptake and sustained public rail use may require more user-aligned rather than one-size-fits-all strategies in such contexts. For this reason, our study develops and tests an integrated structural model linking personality traits, intention to use, social support, and user experience in explaining technology acceptance in rail-based public transportation.

The proposed structural model is grounded in Conservation of Resources (COR) Theory (Halbesleben et al., 2014; Hobfoll, 1989), which provides the theoretical basis for developing the study hypotheses. COR posits that individuals strive to obtain, retain, and protect valuable resources, and that resources may operate in a reinforcing manner, with one facilitating access to or effective use of others. In the present model, the intention to use, social support, and user experience are positioned as key mechanisms through which users mobilize and realize resources under recurring mobility conditions. Intention to Use reflects motivational readiness, Social Support functions as an interpersonal resource that helps users adapt to technology-enabled transport systems, and User Experience reflects whether these resources are translated into ease, comfort, and safety in actual use. Within this logic, personality traits are positioned as dispositional antecedents, while technology acceptance is examined as the continuance-oriented outcome of this broader structural configuration.

The Big Five framework provides a useful basis for explaining stable differences in behavioral tendencies from a dispositional perspective. Personality refers to relatively consistent patterns in how individuals react to and interact with their environments (Specht et al., 2011), making it a meaningful distal predictor of technology-related behavior. The most established taxonomy is the Five-Factor Model, comprising Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism (Goldberg et al., 2006; McCrae and Costa, 2003). Emerging evidence indicates that these traits are relevant to mobility-related settings. For example, conscientiousness and extraversion have been associated with e-bike ownership decisions (Poier et al., 2025), whereas openness and neuroticism have been linked to the acceptance of shared e-scooters (Karami et al., 2025). Although these contexts differ from rail-based public transportation, they support the broader proposition that personality traits may shape the readiness to adopt mobility innovations.

In our study, intention to use is positioned as an early motivational mechanism that reflects an individual's readiness to perform a behavior (Ajzen, 1991) and is commonly treated as a proximal predictor of action (Ajzen and Fishbein, 1980). However, in repeatedly used public transport services, intention alone may not fully explain sustainable acceptance, as users continue to evaluate the system through repeated experiences involving crowding, waiting, transfers, reliability concerns, and digital procedures. Therefore, we treat the intention to use as an initial entry point within a broader structural configuration associated with more stable acceptance.

We treat social support as distinct from mere social influence and define it as emotional, informational, instrumental, and appraisal-based resources derived from social relationships (House, 1981). As an interpersonal resource, it can reduce cognitive burden, strengthen confidence, and facilitate adaptation (Thoits, 2011; Cohen and Wills, 1985), especially in collectivist settings where interpersonal assistance remains an important part of everyday decision making. User experience is the holistic evaluation of commuters' journeys in terms of ease, comfort, and safety across key stages, such as station access, waiting, transfers, navigation, and digital procedures (Göransson and Andersson, 2023; Iseki and Taylor, 2009). Technology acceptance refers to the sustainable acceptance of technology-enabled rail public transportation. It is indicated not only by perceived usefulness and ease of use (Davis, 1989) but also by intention to re-use, emphasizing continued use in line with post-adoption logic in recurring services (Bhattacherjee, 2001).

Based on this framework, our study proposes a differentiated structural process through which personality traits are associated with Technology Acceptance. Extraversion reflects social energy, positive affect, and social stimulation sensitivity. Prior evidence indicates that higher extraversion levels are associated with more favorable perceptions of socially engaging situations (Kocjan et al., 2024). Because rail public transportation environments are socially dense and interaction-intensive, individuals with high extraversion may respond more positively to direct travel experiences. Accordingly, extraversion is expected to positively affect user experience (H1). Openness to experience reflects curiosity, cognitive flexibility, and novelty receptivity. Prior evidence indicates that openness is associated with information-seeking during adaptation (Zhang et al., 2021) and with the perceived availability of social support (Barańczuk, 2019). In digitally enabled rail systems, more open individuals may be more inclined to mobilize interpersonal resources when navigating technology-enabled services. This pathway is also plausible in transport settings, where information sources can shape passengers' evaluations of service attributes and perceived service quality (Romero et al., 2023). Therefore, openness to experience is expected to positively affect social support (H2), which may in turn shape user experience.

In contrast, agreeableness, neuroticism, and conscientiousness are more directly related to intention to use, reflected in users' purpose and plan to use rail-based public transportation. Individuals high in agreeableness tend to favor socially compatible and collectively aligned choices, which may foster a stronger purpose to use shared transport modes (Wang et al., 2021; Riaz and Khan, 2016). Those high in neuroticism are more sensitive to threat and uncertainty, which may encourage clearer usage plans when rail services are perceived as more predictable and controllable (Ahmetoğulları and Rizelioğlu, 2025; Fyhri and Backer-Grøndahl, 2012). Individuals with high conscientiousness tend to be disciplined, structured, and goal-oriented, making them more likely to develop planful and goal-consistent intentions toward rail use (Chen et al., 2025; Luo et al., 2023). Therefore, agreeableness, neuroticism, and conscientiousness are each expected to positively affect intention to use (H3–H5).

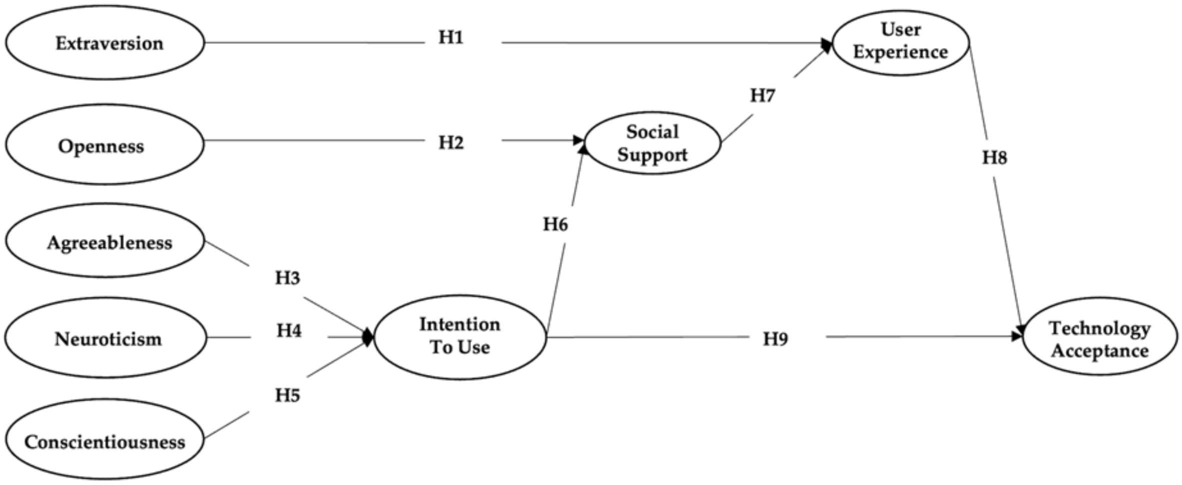

Figure 1 Hypothetical structural model showing the relationships among Big Five personality traits, intention to use, social support, user experience, and technology acceptance. Notes: H1–H9 indicate the proposed hypotheses; arrows represent the hypothesized direct effects between constructs

In the proposed structural model, the intention to use plays both direct and indirect roles in shaping technology acceptance. Indirectly, intention to use may activate social support by prompting users to seek reassurance before engaging with a digitally enabled rail system, particularly in collectivist settings where interpersonal resources are more readily mobilized to reduce uncertainty Yoo et al., 2026; Dang and Xiao, 2022; House, 1981). Accordingly, the intention to use is expected to positively affect social support (H6). Previous evidence suggests that perceived social support can strengthen perceptions of safety and facilitate adaptation under uncertain conditions (Yano et al., 2021). In this context, such support may help users evaluate rail systems more positively in terms of ease, comfort, and safety, thereby strengthening user experience. Therefore, social support is expected to positively affect user experience (H7). In turn, positive user experience is likely to reinforce favorable evaluations of the service, as prior transport research suggests that positive travel experience strengthens acceptance of technology-enabled transport systems (Ko and Park, 2026; Rodwell et al., 2023; Bernhard et al., 2020). Therefore, user experience is expected to positively affect technology acceptance (H8). Directly, because intention to use reflects both purpose and plan, it signals value alignment and readiness for action, which may itself strengthen technology acceptance in repeatedly used rail services (Wei et al., 2025; Ajzen, 1991). Therefore, intention to use is expected to positively affect technology acceptance (H9).

Accordingly, this study examines the technology acceptance of rail-based public transportation in the Jakarta metropolitan area through an integrated structural path model that links the Big Five personality traits, namely, intention to use, social support, user experience, and continuance-oriented technology acceptance in Indonesia's collectivist context. This study makes three main contributions. First, it advances research on public transport acceptance by moving beyond a single-route view of adoption and proposes a differentiated structural framework through which personality traits are associated with technology acceptance. Second, acceptance is conceptualized as continuance-oriented by incorporating intention to reuse into the explanation of sustained rail use. Third, it evaluates whether the proposed personality-based structural model offers greater explanatory depth than a baseline acceptance model in an urban collectivist setting. In practical terms, the study provides a basis for more user-aligned approaches to strengthening public rail uptake and sustained acceptance. Figure 1 presents the proposed structural model of technology acceptance in rail-based public transportation.

2. Methods

2.1 Research Design

This study employed a cross-sectional, quantitative survey-based design. Data were collected between May and July 2024 to examine the relationships among personality traits, intention to use, social support, user experience, and technology acceptance in rail-based public transport.

2.2 Sample Collection and Data Collection

The target population comprised rail-based public transport users (KRL and MRT) in the Jakarta metropolitan area. A purposive sampling technique was applied, requiring respondents to have prior experience using KRL or MRT services. Data were collected through an online questionnaire distributed through a digital survey platform. A total of 605 responses were received, of which 584 (97%) were retained after data screening, whereas 21 responses (3%) were excluded due to incomplete information. The demographic profile of the respondents was as follows:

- Age: <18 years (64), 18–25 years (435), 26–35 years (49), 36–45 years (22), 46–65 years (14).
- Gender: Male (326; 56%) and female (258; 44%).
- Occupation: Private sector employees (18%), civil servants (1%), entrepreneurs (4%), secondary school students (15%), higher education students (60%), and others (2%).

The final sample size (n = 584) exceeded the minimum requirement for Structural Equation Modeling (SEM), ensuring stable parameter estimation (Hair et al., 2019). The critical N (CN) criterion further supported sample adequacy, with values $\geq$ 200 indicating sufficient model representativeness (Kline, 2015; Hoelter, 1983).

2.3 Measurement and Instrumentation

All constructs were measured using instruments adapted from established literature and assessed on a five-point Likert scale (1 = strongly disagree; 5 = strongly agree).

1. The Big Five Personality Traits were measured using the Big Five Inventory (BFI) (John and Srivastava, 1999), a self-report instrument designed to assess the five core personality dimensions (Extraversion, Openness, Agreeableness, Neuroticism, and Conscientiousness). The BFI has been widely used and validated in personality research and survey studies to reliably capture dispositional traits.
2. The intention to use was assessed through separately conceptualized dimensions of purpose (6 items) and plan (5 items).
3. Social support was measured using 18 items adapted from (House, 1981) and (Franken, 2002), representing emotional, instrumental, informational, and appraisal support.
4. The user experience comprised 15 items reflecting three dimensions: ease, comfort, and safety.
5. Technology acceptance was measured using 15 items covering perceived usefulness (PU), perceived ease of use (PEOU), and intention to re-use, consistent with measurement approaches in the Technology Acceptance Model (TAM) and information systems research.

A pilot study involving 96 respondents demonstrated high internal consistency, with Cronbach's alpha values ranging from 0.895 to 0.966. The questionnaire consisted of 184 items, and respondents required approximately 15–20 minutes to complete the survey.

2.4 Data Analysis

Data analysis was conducted using LISREL 8.72 (Jöreskog and Sörbom, 1993) using a two-stage procedure. Confirmatory Factor Analysis (CFA) was performed to assess construct validity and reliability. Second, Structural Equation Modeling (SEM) was applied to test the hypothesized relationships among variables.

Model fit was evaluated using multiple goodness-of-fit indices: normed chi-square (X^2/df $\leq$ 5.0), RMSEA ($\leq$ 0.06, with values up to 0.08 considered acceptable), SRMR ($\leq$ 0.08), CFI ($\geq$ 0.95), and Critical N ($\geq$ 200). Path significance was assessed using t-values greater than 1.96 ($p < 0.05$) or 2.58 ($p < 0.01$). This analytical procedure enabled a rigorous evaluation of both the measurement model and the structural relationships proposed in the study.

3. Result

To enhance the readability of the structural relationships, Figure 2 presents a graphical abstract summarizing the main pathways.

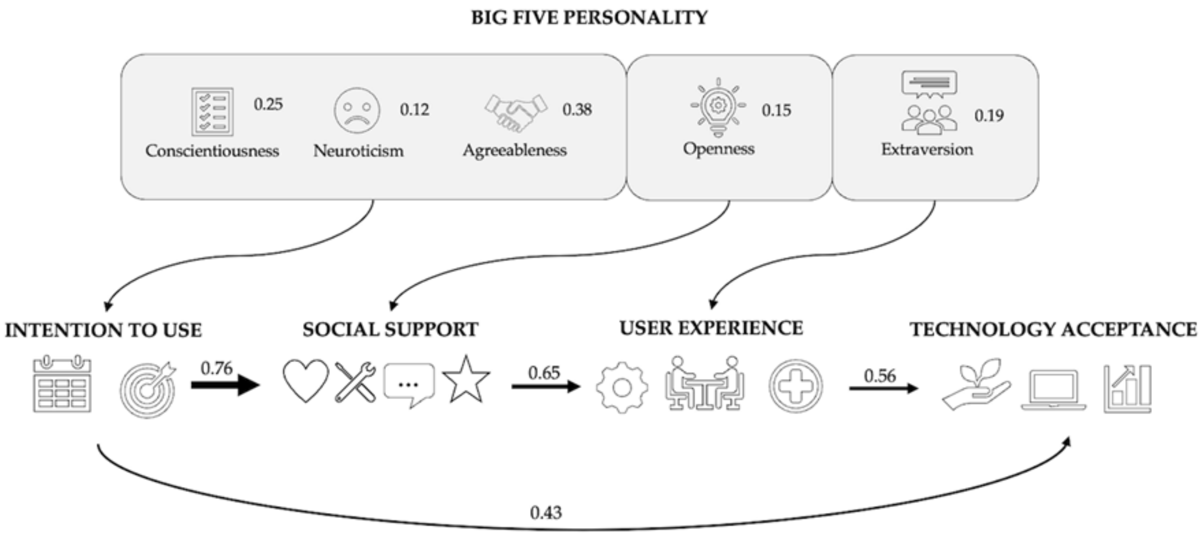

Figure 2 Graphical abstract of resource-based pathways to technology acceptance

3.1 Descriptive Statistics and Correlations

The descriptive statistics, reliability, and inter-construct correlations are presented in Table 1. All constructs demonstrate excellent internal consistency, with Cronbach's α ranging from 0.919 to 0.961, confirming the measurement instruments' reliability. Among the Big Five traits, conscientiousness has the highest mean value (M = 4.07, SD = 0.63), indicating a relatively strong orientation toward discipline and responsibility within the sample. In contrast, neuroticism recorded the lowest mean (M = 3.09, SD = 0.89), indicating comparatively lower levels of emotional instability.

Correlation analysis revealed patterns consistent with the proposed model. Agreeableness exhibited a moderate positive correlation with intention to use (r = 0.526, $p < 0.01$), while conscientiousness and openness exhibited moderate correlations with intention to use (r = 0.504 and r = 0.487, respectively; $p < 0.01$). Notably, social support is strongly correlated with user experience (r = 0.702, $p < 0.01$) and technology acceptance (r = 0.753, $p < 0.01$), highlighting its central role in the model. Intention to use also demonstrates a strong association with social support (r = 0.807, $p < 0.01$). In contrast, neuroticism showed weak correlations with most constructs ($r \leq 0.111$, $p < 0.01$). Overall, these results provide an adequate empirical basis for conducting CFA.

Table 1 Correlation matrix

No	Latent Variable	Mean (SD)	# of Item	1	2	3	4	5	6	7	8	9
1	Agreeableness	3.87 (0.56)	25	(0.919)								
2	Neuroticism	3.09 (0.89)	25	0.111**	(0.961)							
3	Extraversion	3.75 (0.62)	25	0.728**	0.004**	(0.934)						
4	Conscientiousness	4.07 (0.63)	25	0.716**	-0.003**	0.677**	(0.955)					
5	Openness	3.86 (0.59)	25	0.716**	0.112**	0.709**	0.756**	(0.929)				
6	Intention to Use	3.77 (0.76)	11	0.526**	0.105**	0.486**	0.504**	0.487**	(0.924)			
7	Social Support	3.83 (0.72)	18	0.527**	0.086**	0.464**	0.527**	0.534**	0.807**	(0.958)		
8	User Experience	3.94 (0.69)	15	0.521**	0.035**	0.472**	0.523**	0.458**	0.623**	0.702**	(0.939)	
9	Technology Acceptance	3.92 (0.74)	15	0.522**	0.079**	0.455**	0.493**	0.477**	0.753**	0.753**	0.773**	(0.945)

Note: N = 584. Values below the diagonal represent Pearson correlation coefficients among latent variables. Values in parentheses on the diagonal indicate Cronbach's alpha reliability coefficients for each construct.$**p < 0.01$ and $*p < 0.05$ indicate statistically significant correlations based on two-tailed tests.

3.2 Measurement model (CFA)

3.2.1 Reliability and Convergent Validity

Table 2 shows that all constructs demonstrate satisfactory reliability and convergent validity. Cronbach's alpha values exceeding the recommended threshold of 0.70 range from 0.919 to 0.961. The composite reliability values also surpass 0.70 (0.914–0.958), while the average variance extracted values are above 0.50 (0.685–0.916). These results indicate that all constructs adequately capture variance from their respective indicators.

Table 2 Reliability and convergent validity

Latent Variable	Cronbach's Alpha ≥ 0.70	CR ≥ 0.70	AVE ≥ 0.50
Agreeableness	0.919	0.933	0.735
Neuroticism	0.961	0.914	0.685
Extraversion	0.934	0.927	0.719
Conscientiousness	0.955	0.958	0.822
Openness	0.929	0.938	0.755
Intention to Use	0.924	0.956	0.916
Social Support	0.958	0.953	0.834
User Experience	0.939	0.943	0.847
Technology Acceptance	0.945	0.929	0.814

Note: N = 584. Cronbach's alpha was used to assess internal consistency reliability, with values ≥ 0.70 indicating acceptable reliability. CR = composite reliability, with values ≥ 0.70 indicating adequate construct reliability. AVE = average variance extracted, with values $\geq$ 0.50 indicating acceptable convergent validity. (Hair et al., 2019).

3.2.2 Factor Loadings

Table 3 presents the standardized factor loadings and corresponding t-values. All indicators significantly impacted their respective constructs ($\lambda \geq 0.50, t > 2.58, p < 0.01$). The lowest loading was observed for anxiety under neuroticism ($\lambda = 0.57$), whereas the highest loading was observed for self-discipline under conscientiousness ($\lambda = 0.98$). Within technology acceptance, the intention to reuse demonstrates a high factor loading ($\lambda = 0.87; t = 20.69$), indicating that acceptance in the public transport context extends beyond perceived usefulness and ease of use to encompass continuance-oriented behavior. This finding supports the operationalization of technology acceptance as continuance acceptance rather than mere initial adoption.

Table 3 CFA factor loadings and t-values

Latent Variable	Indicator	Factor Loading	t-value
Agreeableness	Compassion	0.85	18.10
	Trust	0.85	15.22
	Cooperation	0.87	14.12
	Modesty	0.80	15.13
	Tolerance	0.92	15.82
Neuroticism	Anxiety	0.57	8.61
	Depression	0.79	18.92
	Anger	0.87	20.06
	Vulnerability	0.96	21.47
	Emotional volatility	0.89	19.56
Extraversion	Sociability	0.80	12.70
	Assertiveness	0.80	15.78
	Activity level	0.89	14.23
	Positive emotions	0.91	17.63
	Warmth	0.84	17.85
Conscientiousness	Organization	0.87	14.94
	Responsibility	0.94	19.27
	Self-discipline	0.98	16.41
	Achievement orientation	0.88	19.99
	Deliberation	0.86	18.20
Openness	Imagination	0.89	11.87
	Aesthetic appreciation	0.73	13.69
	Intellectual curiosity	0.97	19.58
	Preference for variety	0.96	17.71
	Openness to feelings	0.78	12.53
Intention to Use	Purpose	0.96	17.27
	Plan	0.96	19.53
Social Support	Emotional	0.95	20.60
	Instrumental	0.94	20.78
	Informational	0.86	19.86
	Appraisal	0.89	20.54
User Experience	Ease	0.88	17.75
	Comfort	0.91	19.15
	Safety	0.97	20.84
Technology Acceptance	Perceived Usefulness	0.95	20.96
	Intention to reuse	0.87	20.69
	Perceived easy to use	0.89	19.09

Note: All factor loadings are statistically significant and above the minimum threshold of 0.50 ($t > 1.96$, $p < 0.05$; all exceed $t > 2.58$, $p < 0.01$).

3.2.3 Discriminant Validity

The Fornell–Larcker criterion is used to establish discriminant validity (Table 4). The square root of AVE exceeds the corresponding inter-construct correlations for all constructs. For example, the $\sqrt{\text{AVE}}$ for agreeableness (0.857) is greater than its highest correlation with other constructs, and similar patterns are observed for Intention to Use ($\sqrt{\text{AVE}} = 0.957$) and technology acceptance ($\sqrt{\text{AVE}} = 0.902$). These results confirm the conceptual distinctiveness of all constructs.

To further assess the potential overlap among the predictors, collinearity diagnostics were examined. The variance inflation factor values for the predictors of intention to use ranged from 1.003 to 1.795, indicating that multicollinearity is not a concern.

Table 4 Discriminant validity (Fornell–Larcker criterion)

No	Latent Variable	1	2	3	4	5	6	7	8	9
1	Agreeableness	**0.857**								
2	Neuroticism	0.111**	**0.828**							
3	Extraversion	0.728**	0.004**	**0.848**						
4	Conscientiousness	0.716**	-0.003**	0.677**	**0.907**					
5	Openness	0.716**	0.112**	0.709**	0.756**	**0.869**				
6	Intention to Use	0.526**	0.105**	0.486**	0.504**	0.487**	**0.957**			
7	Social Support	0.527**	0.086**	0.464**	0.527**	0.534**	0.807**	**0.913**		
8	User Experience	0.521**	0.035**	0.472**	0.523**	0.458**	0.623**	0.702**	**0.920**	
9	Technology Acceptance	0.522**	0.079**	0.455**	0.493**	0.477**	0.753**	0.753**	0.773**	**0.902**

Note: The diagonal values represent the square root of the average variance extracted ($\sqrt{\text{AVE}}$). The off-diagonal values represent the correlations among the constructs. Discriminant validity is established when the diagonal values ($\sqrt{\text{AVE}}$) exceed the corresponding inter-construct correlations (Fornell and Larcker, 1981).

3.3 Structural Model

The structural model demonstrates an excellent fit with the empirical data ($X^2/\text{df} = 2.342$, RMSEA = 0.048, CFI = 0.99, SRMR = 0.048, CN = 286.41), indicating that the proposed model adequately represents the observed relationships. All model fit indices meet the recommended thresholds, indicating a well-fitting model without signs of overfitting.

To assess common method bias (CMB), Harman's single-factor test shows that the first factor explains only 26.48% of the total variance, well below the 50% threshold. In addition, a one-factor model exhibited extremely poor fit ($X^2/\text{df} = 35.979$, RMSEA = 0.245), and all inter-construct correlations remained below 0.85. Collectively, these results indicate that CMB is unlikely to materially influence the findings.

Table 5 summarizes the results of the hypothesis testing. All nine hypothesized paths are statistically significant ($\beta = 0.12$–0.76, $p < 0.01$) and consistent with the proposed directions. The strongest effects are observed along the core sequential pathway from Intention to Use → Social Support → User Experience → Technology Acceptance, highlighting the central role of social and experiential mechanisms in shaping technology acceptance.

To further facilitate the interpretation of the structural relationships, Figure 3 presents an effect-size map summarizing standardized path coefficients. This visualization provides a compact overview of the standardized path coefficients and clearly illustrates the distinct pathways within the model. In particular, it highlights the dominant influence of intention to use on social support ($\beta = 0.76$), followed by the sequential effects of social support on user experience ($\beta = 0.65$) and user experience on technology acceptance ($\beta = 0.56$). It also shows differentiated entry points from personality traits, where agreeableness, conscientiousness, and neuroticism influence intention to use, whereas openness and extraversion operate through alternative pathways.

Table 5 Summary of hypotheses testing (structural model)

Hypothesis	Path	Estimate (β)	t-value	Result
H1	Agreeableness → Intention to Use	0.38	6.91	Supported
H2	Neuroticism → Intention to Use	0.12	3.55	Supported
H3	Conscientiousness → Intention to Use	0.25	4.54	Supported
H4	Openness → Social Support	0.15	5.21	Supported
H5	Extraversion → User Experience	0.19	5.53	Supported
H6	Intention to Use → Social Support	0.76	24.14	Supported
H7	Intention to Use → Technology Acceptance	0.43	13.26	Supported
H8	Social Support → User Experience	0.65	17.37	Supported
H9	User Experience → Technology Acceptance	0.56	16.58	Supported

Note: All hypothesized paths are significant at $p < 0.01$ ($t > 2.58$).

Predictor → Outcome	**Intention to Use**	**Social Support**	**User Experience**	**Technology Acceptance**
Agreeableness	0.38	–	–	–
Neuroticism	0.12	–	–	–
Conscientiousness	0.25	–	–	–
Openness	–	0.15	–	–
Extraversion	–	–	0.19	–
Intention to Use	–	0.76	–	0.43
Social Support	–	–	0.65	–
User Experience	–	–	–	0.56

Figure 3 Effect-size map of standardized path coefficients. Note: Shading indicates the magnitude of standardized path coefficients (β): light yellow = weak (0.10–0.29), orange = moderate (0.30–0.59), and red = strong ($\geq$ 0.60).

Explained variance (R^2) values for endogenous constructs are summarized in Figure 4. Intention to Use achieves $R^2 = 0.36$, explained by agreeableness, neuroticism, and conscientiousness. Social support shows substantial explanatory power ($R^2 = 0.72$), driven by openness and intention to use. User experience reaches $R^2 = 0.58$, explained by extraversion and social support, while technology acceptance reached a substantial $R^2 = 0.79$, explained by intention to use and user experience.

R^2 values indicate the proportion of variance explained in each endogenous construct. According to the established SEM guidelines, values around 0.25 are considered weak, 0.50 moderate, and 0.75 substantial (Hair et al., 2019). In this study, most R^2 values exceed the moderate threshold and several reached substantial levels, indicating that the model demonstrates strong explanatory power in capturing the proposed structural relationships.

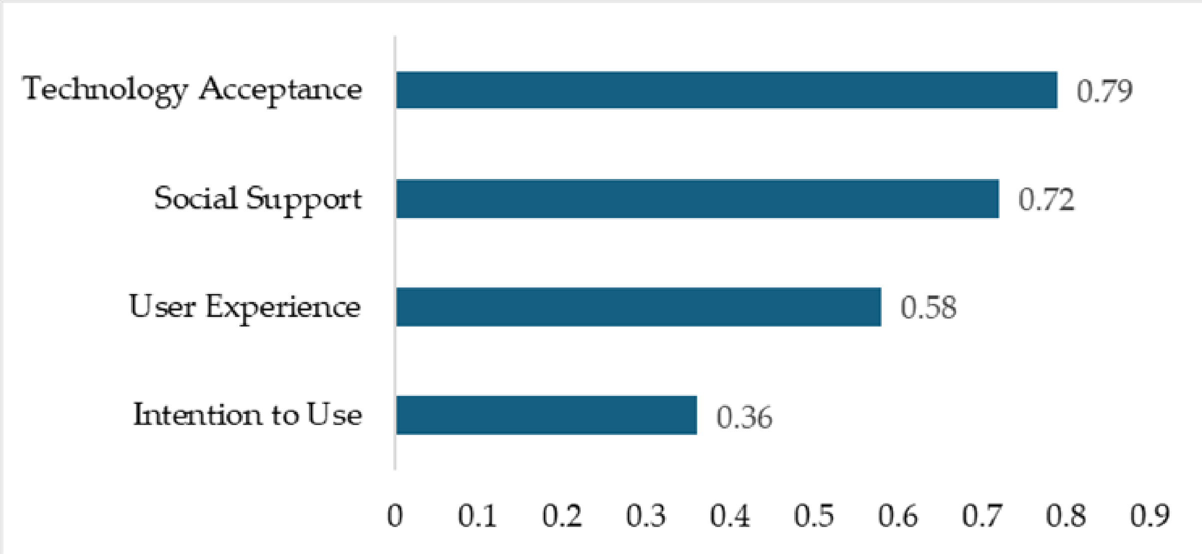

Figure 4 Explained variance (R^2) across endogenous constructs

4. Discussion

4.1 Main Interpretation

The results support all hypothesized relationships, with all structural paths reaching statistical significance. The variability in effect sizes reveals differentiated mechanisms underlying technology acceptance rather than a uniform pattern of association. The model demonstrates moderate to substantial explanatory power (Kline, 2023; Hair et al., 2019), particularly for social support ($R^2 = 0.72$), user experience ($R^2 = 0.58$), and technology acceptance ($R^2 = 0.79$). These findings indicate that the model provides a robust explanatory framework for understanding the acceptance of technology in rail-based public transportation. However, these findings should be interpreted in light of the student- and young adult-dominant sample, which may limit their generalizability to broader commuter populations.

Although several personality traits exhibit moderate to high inter-correlations, this pattern is theoretically expected within the Big Five framework. These dimensions are conceptually distinct but empirically related because of shared higher-order structures and overlapping behavioral tendencies (Soto and John, 2017; DeYoung, 2006). The relatively homogeneous and student-dominant sample may further contribute to this convergence. These correlations do not indicate construct redundancy. The Fornell–Larcker criterion is used to support discriminant validity, and collinearity diagnostics confirm that multicollinearity is not a concern, with all VIF values remaining within acceptable thresholds (Hair et al., 2019).

The findings reveal that technology acceptance pathways are structured through multiple entry points. Specifically, agreeableness, conscientiousness, and neuroticism are associated with intention to use, whereas openness is associated with social support and extraversion with user experience. This pattern indicates that different personality traits operate through distinct entry points within the acceptance process, rather than following a single pathway, as further illustrated by the total indirect effects of each personality trait presented in Figure 5.

As shown in Figure 5, agreeableness exhibits the strongest mediated influence, followed by Conscientiousness, while Openness shows the weakest contribution, indicating that personality traits differ not only in their entry points but also in the strength of their mediated influence. Building on this pattern, the findings suggest a layered progression across motivational, social, and experiential processes. Intention to Use functions as a bridging resource connecting dispositional traits with downstream mechanisms. Social support acts as a transmission layer through which initial motivational readiness becomes socially embedded, and user experience reflects the experiential realization of these processes. In this framework, technology acceptance is interpreted as continuance-oriented acceptance, emphasizing sustained use rather than initial trial in recurring mobility contexts. Overall, by integrating dispositional, motivational, social, and experiential components within a unified framework, the study provides a more comprehensive and context-sensitive understanding of technology acceptance that extends beyond conventional linear models.

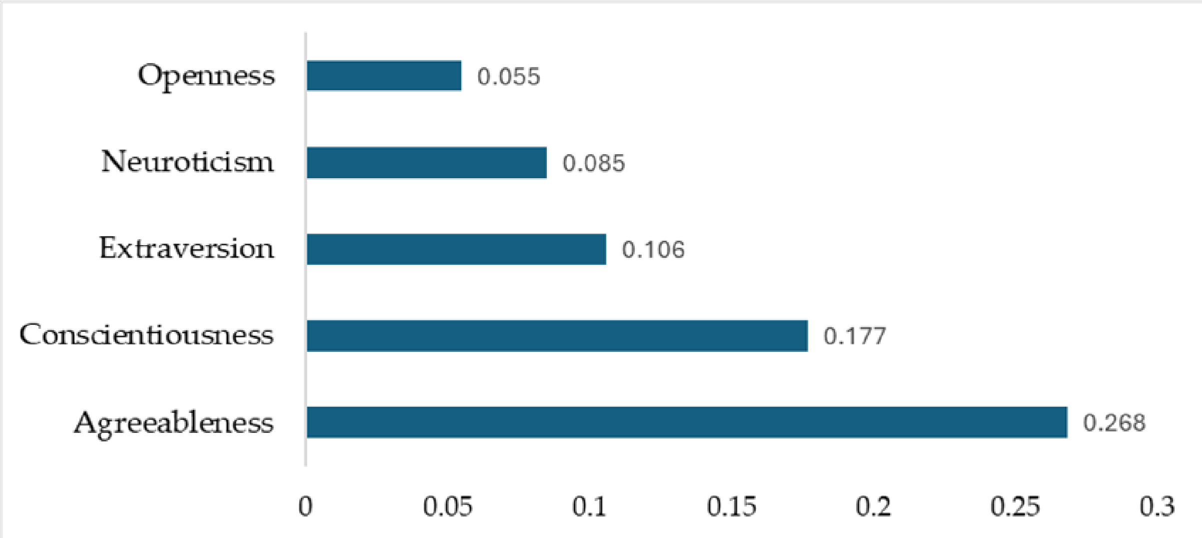

Figure 5 Decomposition of the mediation of personality traits on technology acceptance

4.2 Personality traits and intention to use

Agreeableness, conscientiousness, and neuroticism are significantly associated with intention to use, indicating that cooperative orientation, goal-directedness, and emotional regulation shape early motivational readiness. These findings are consistent with prior studies showing that personality traits influence core constructs of the Technology Acceptance Model (Svendsen et al., 2013; McElroy et al., 2007) and behavioral intention across diverse domains (Chen et al., 2025; Rizun et al., 2024). Although neuroticism is significantly associated with intention to use, its effect size is smaller than those of agreeableness and conscientiousness. This indicates that within this context, neuroticism plays a more limited role in intention formation. While it contributes to the model, its influence appears secondary to more structured and goal-oriented traits. Overall, the results extend prior evidence to the context of public rail transport, reinforcing the role of personality traits as dispositional antecedents of intention formation, albeit with differentiated levels of predictive strength.

4.3 Distinct Pathways: Openness, Social Support, Extraversion, and User Experience

This study reveals two distinct personality-driven pathways that have remained underexplored in prior technology acceptance research. First, openness is indirectly associated with technology acceptance indirectly through social support, suggesting that individuals with high openness rely on social validation and shared experiences before forming enriched user experiences. While previous research has linked openness to social outcomes (Morstead et al., 2024), this study demonstrates its specific role in mobilizing social support within technology acceptance processes.

Second, extraversion is directly associated with user experience, consistent with evidence that extraverted individuals engage more actively with interactive systems and social environments (Kabacińska et al., 2025; Völkel et al., 2022). Extraversion facilitates social interaction and engagement during travel in the context of public transport, thereby enhancing experiential evaluations. These findings highlight that personality traits shape acceptance not only through intention but also through socially and experientially grounded mechanisms.

4.4 Intention to Use, Social Support, and User Experience

Another key contribution is the repositioning of the intention to use as a central resource within the model rather than merely an outcome. While prior studies typically conceptualize social support as an antecedent of intention (Abbasi et al., 2025; Wang et al., 2024), the present findings indicate that the use intention is associated with social support and user experience. This pattern reflects a sequential configuration of motivational, social, and experiential processes consistent with the Conservation of Resources framework, in which early motivational readiness is linked to the development of social and experiential resources within the technology acceptance process. These findings indicate that technology acceptance emerges through interconnected psychological, social, and experiential dimensions rather than representing a single linear mechanism.

Although the model specifies the intention to use as the preceding social support, alternative directional configurations are statistically testable. Supplementary analysis of the reverse path (User Experience → Social Support) yielded a statistically significant but modest negative coefficient ($\beta = -0.13$), suggesting that more positive experiential evaluations are associated with a slightly lower reliance on social support. However, the magnitude of this effect is limited and does not alter the structural configuration examined in this study. Overall, the results support the positioning of Intention to Use as a bridging construct within the model, linking dispositional traits to socially embedded support and experiential outcomes in shaping technology acceptance.

4.5 User Experience, Intention to Use, and Acceptance of Continuance

User experience and intention to use exert direct effects on Technology Acceptance, confirming that ease, comfort, and perceived utility distinguish sustainable adoption from weaker acceptance or non-adoption (Rodwell et al., 2023; Hart and Sutcliffe, 2019). Beyond classical TAM constructs, this study incorporates the intention to reuse as a core indicator, thereby conceptualizing acceptance as continuance acceptance rather than the initial trial. Consistent with the findings of (Sumaedi et al., 2016) and (Ferriès et al., 2026), the findings emphasize that sustainable public transport systems depend on users' willingness to repeatedly rely on the service over time.

4.6 Practical Implications

The findings offer several practical implications. First, given the central mediating role of social support, service providers should actively foster supportive environments through instrumental (feeder services, fare incentives), emotional (group travel programs), informational (real-time applications and responsive chatbots), and appraisal-based mechanisms (loyalty rewards). Such strategies can strengthen collective engagement and sustain ridership (Liu et al., 2025; Guzman et al., 2024; Shiddiqi et al., 2024; Zarabi et al., 2024).

Second, the direct influence of extraversion on user experience highlights the importance of maintaining high-quality travel environments. Digital communities, gamification features, and offline engagement initiatives may enhance experiential value not only for extraverted users but also for the broader passenger base (Vacondio et al., 2025; Avril et al., 2024).

Third, strengthening the intention to use is critical because a weak initial intention may weaken the sequential development of social and experiential resources. Educational campaigns, trial incentives, and corporate commuting programs can help build early confidence and collective readiness to adopt public rail transport (Zarabi et al., 2024; Franssens et al., 2021.

Finally, the inclusion of Intention to Re-Use underscores that the success of sustainable public transport requires systems that are fit-to-users, ergonomic, user-friendly, adaptive, and technologically integrative (Sogbe et al., 2025; Ardi et al., 2024; Suzianti and Shafira, 2021;

Inturri et al., 2021). Taken together, these findings indicate that user experience functions as the final experiential mechanism associated with sustained technology acceptance in rail public transportation.

5. Limitations and Future Research

Several limitations should be acknowledged. The study focuses on the Jabodetabek region, which may limit the generalizability to other contexts or transport modes. This study is based on cross-sectional data, which does not capture the temporal dynamics among the modeled constructs. Future research is encouraged to further examine resource-related dynamics using alternative designs, such as longitudinal studies.

In addition, the sample is student-dominant, with approximately 75% of the respondents being students or young adults. Although this group represents a significant segment of rail-based commuters in the Jakarta metropolitan area, their commuting patterns, social interaction structures, and resource constraints may differ from those of other demographic groups. Accordingly, the findings should be interpreted with caution when considering commuter populations beyond this demographic profile. To enhance generalizability, future studies should include more occupationally and demographically diverse samples. Further research may also extend this line of inquiry by exploring cross-cultural and cross-modal contexts, incorporating service and policy variables, and employing mixed-method or experimental approaches to capture the interplay among personality traits, social support, and user experience.

6. Conclusions

This study demonstrates that acceptance of technology in rail-based public transportation is associated with distinct, resource-based pathways shaped by personality traits, social support, and user experience. Instead of following a single linear route, acceptance appears to be structured through a multi-entry configuration in which different personality traits enter the process at different stages. These conclusions should be interpreted with appropriate caution, given the student- and young adult-dominant sample. This study advances technology acceptance research by proposing a structured, multi-layered explanation of how acceptance may develop in recurring mobility contexts. Within this structure, Intention to Use functions as a bridging motivational mechanism that connects dispositional traits with downstream social and experiential mechanisms, whereas social support operates as a transmission layer through which early motivational readiness becomes socially embedded and is subsequently reflected in User Experience. Furthermore, technology acceptance is conceptualized as continuance-oriented acceptance, emphasizing sustained use as the relevant outcome rather than the initial trial. By integrating dispositional, motivational, social, and experiential layers within a single framework, this study offers a more comprehensive and context-sensitive understanding of technology acceptance than conventional linear models. From a practical perspective, the findings indicate that sustainable adoption depends not only on system performance but also on the social and experiential conditions that support users over time.

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Author Contributions

Hwi-Chie Ho: Conceptualization, Methodology, Formal Analysis, Data Curation, Software, Writing-Original Draft, Writing-Review and Editing, Supervision, Funding Acquisition. Amir Tjolleng: Data Curation, Software, Writing-Review and Editing, Project Administration. Dyah

Lestari Widaningrum: Data Collection, Data Curation. Harjanto Prabowo: Writing-Reviewing and Editing. Bertha Maya Sopha: Writing-Review and Editing.

Conflict of Interest

The authors declare no conflicts of interest.

Declaration of AI

During the preparation of this manuscript, the authors used ChatGPT as a language assistance tool to improve clarity and readability. All content was critically reviewed, edited, and approved by the authors, who take full responsibility for the accuracy, integrity, and originality of the work.

Supplementary Materials

The data that support the findings of this study are openly available in https://zenodo.org/records/18009355.

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