# Cyclist behavior analysis on the perception of self and others: a structural equation modeling approach

Che An LIN [a], Yu Ting HSU [b]

[a,b] *Department of Civil Engineering, National Taiwan University, 10617, Taiwan*
[a] *E-mail: r12521514@ntu.edu.tw*
[b] *E-mail: yutinghsu@ntu.edu.tw*

**Abstract**: Cycling is a sustainable urban transport mode, but inadequate infrastructure forces cyclists to share roads with vehicles and pedestrians, increasing conflicts and safety concerns. This study explores how psychological factors shape cyclists' perceptions and behaviors using Structural Equation Modeling (SEM) based on the Theory of Planned Behavior (TPB). Key factors include attitudes, habits, moral norms, risk perception, and environmental influences. A questionnaire survey was conducted at National Taiwan University (NTU), where intense bicycle usage has led to considerable conflicts between cyclists, pedestrians, and other vehicles, and disorderly parked bicycles can be frequently observed on the campus. The modeling results of SEM indicate that negative attitudes reduce behavioral intention, while habits positively influence it. Attitudes also shape how cyclists perceive their own and others' behaviors, whereas habits and risk perception negatively impact these assessments. The findings highlight the need for improved infrastructure, educational campaigns, and positive attitude reinforcement to promote safer and more inclusive cycling environments, where self-aware and regulated cycling culture is also an underlying issue.

*Keywords*: Cycling behavior; Cyclist perception; Structural equation model; Traffic management

## 1. INTRODUCTION

Urban cycling has emerged as an essential mode of transportation, offering significant economic and environmental benefits. The rise in bicycle usage contributes to reduced traffic congestion, lower carbon emissions, and improved public health. However, the increasing number of bicycles has also introduced several challenges, including congestion during peak hours, frequent accidents, and parking difficulties (similar to other motorized vehicles while at a relatively lower level). These issues are exacerbated by the inadequacy of cycling infrastructure, leading to a sense of insecurity among cyclists and marginalization in urban traffic systems. Understanding cyclist behavior underlying cycling traffic, particularly how individuals perceive their own behavior and that of others, is critical for developing effective urban cycling policies. The Theory of Planned Behavior (TPB) provides a robust framework for analyzing the psychological determinants influencing cycling behavior. This study extends TPB by constructing a Structural Equation Model (SEM) to explore the psychological factors affecting behavioral intention, self-assessment of cycling behavior, and the relationship between the perception of self and others. Accordingly, this research aims to provide insights into effective policy-making and infrastructure planning to promote safe and sustainable urban cycling.

Urban cycling has gained prominence as cities promote sustainable transport systems. Previous studies have highlighted that increased cycling can reduce urban congestion and lower carbon footprints (Pucher & Buehler, 2012). Additionally, cycling offers health benefits by promoting active lifestyles and reducing risks associated with sedentary behaviors (Garrard, Rissel, & Bauman, 2012). However, the surge in cycling activities has also led to increased competition for road space, raising concerns over cyclist safety and infrastructure adequacy (Heinen et al., 2010).

The rapid expansion of urban cycling has introduced several challenges, including congestion during peak hours, frequent conflicts (or even accidents), and inadequate parking facilities. Studies indicate that the lack of designated cycling lanes and improper traffic management contribute significantly to safety concerns among cyclists (Aldred et al., 2016). In particular, the risk of accidents at intersections and interactions with motorized vehicles are key deterrents to cycling adoption (Schepers et al., 2017). Furthermore, limited parking infrastructure exacerbates space conflicts between cyclists and pedestrians (Pucher et al.,, 2010).

Facing the challenges that involve complex interactions between cyclists and others (pedestrians, other vehicles, and cyclists themselves) in given environmental settings, it is essential to understand cyclists' behavior underlying how they perceive the environment and interact with others, so as to attain better management strategies. Hence, the TPB is adopted as it is a widely used framework for understanding travel behavior, including cycling. TPB posits that behavioral intention is influenced by attitudes, subjective norms, and perceived behavioral control (Ajzen, 1991). Research has demonstrated that attitudes toward cycling, such as perceived safety and convenience, significantly impact individuals' likelihood of choosing cycling as a transport mode (Heinen et al., 2011). Additionally, social norms, such as peer influence and community support, shape cycling behaviors as well (Chataway et al., 2014). Structural Equation Modeling (SEM) has been increasingly applied in transport research to examine complex relationships between psychological factors and travel behavior (De Vos et al., 2019). SEM enables researchers to assess latent variables such as perception, attitude, and behavioral intention, providing in-depth insights into the underlying motivations behind cycling decisions. Studies have used SEM to investigate the relationship between safety perceptions and cycling frequency, demonstrating that perceived risk significantly influences cycling participation (Nikitas, 2018).

An important aspect of cycling behavior is how cyclists perceive themselves and others on the road. Previous research suggests that self-perception of rule adherence and risk-taking behavior influences how cyclists judge others' behavior (Johnson et al., 2013). Studies have also found that perceived behavior of other cyclists affects individual compliance with traffic rules and risk-taking tendencies (Götschi et al., 2016). Understanding these psychological dynamics is crucial for designing interventions that promote safer cycling practices.

Based on the literature, addressing the challenges of urban cycling requires an integrated approach involving infrastructure improvement, behavior-focused policies, and education campaigns. Governments and city planners should focus on expanding cycling infrastructure, implementing traffic-calming measures, and promoting a positive cycling culture through targeted behavioral interventions (Piatkowski et al., 2017). Additionally, leveraging psychological insights from TPB and SEM can aid in designing policies or even fostering the culture that encourages safer cycling behaviors while addressing public concerns about safety and convenience.

## 2. METHODOLOGY

### 2.1 Questionnaire Design

A structured questionnaire was developed to collect data on demographic characteristics (age, gender, education level, and cycling frequency, etc.) and various constructs related to cycling behaviors, which were divided into riding behavior and parking behavior. These constructs included Attitude (AT), Behavioral Intention (BI), Moral Norms (MN), Effect of Others (EO), Risk Perception (RP), Self-behavior Assessment (SA), Environmental Perception (EP), and Assessment of Others' Behavior (OBA). The measurement items of riding and parking models are shown in Tables 1 and 2.

Table 1. Measurement items of riding model

| Latent variables | | Indicators |
|---|---|---|
| Attitude | AT1 | Do you think you have the need to ride a bicycle on campus? |
| | AT2 | Do you often ride a bicycle? |
| | AT3 | Do you often ride a bicycle on campus? |
| Moral norm | MN1 | Do you consider speeding inappropriate? |
| | MN2 | Do you consider maintaining safe distance appropriate? |
| | MN3 | If your riding behavior could endanger others, would you avoid such behavior? |
| Risk perception | RP1 | Are you concerned about collisions with pedestrians or cars? |
| | RP2 | Are you concerned about accidents due to lack of riding skills? |
| | RP3 | Do you think the road layout poses a danger? |
| | RP4 | Do you think the geometry of intersections poses a danger? |
| Behavioral intention | BI1 | Do you ever take your hands off the handlebars? |
| | BI2 | Do you ever ride side by side with another cyclist? |
| | BI3 | Do you ever use your phone while riding? |
| | BI4 | Do you ever carry a passenger on your bicycle? |
| | BI5 | Do you ride with an umbrella when it's raining? |
| Environment perception | EP1 | Do you find it safe to ride a bicycle on campus? |
| | EP2 | Does riding a bicycle on campus make you feel pressured? |
| | EP3 | Do you think the riding environment on campus is friendly? |
| | EP4 | Do you find the road environment on campus comfortable? |
| | EP5 | Do you think the bike lane planning on campus is adequate? |
| | EP6 | Do you think the campus lighting is sufficient? |
| | EP7 | Do you think the campus has adequate deceleration facilities for bikes? |
| | EP8 | Do you think the road design on campus is friendly to bicycle riding? |
| Effect of others | EO1 | If you see others engaging in dangerous riding behavior, would you avoid similar riding behaviors? |
| | EO2 | If you witness cases of riding accidents, would you therefore avoid similar riding behaviors? |
| | EO3 | Do you try to follow good riding behavior demonstrated by others as much as possible? |
| Self-behavior | SBA1 | Do you consider your riding behavior safe? |

| | | |
|---|---|---|
| assessment | SBA2 | Do you consider your riding behavior law-abiding? |
| | SBA3 | Do you consider yourself a good cyclist? |
| Others' behavior assessment | OBA1 | Do you consider the riding behavior of others on campus to be safe? |
| | OBA2 | Do you consider the riding behavior of others on campus to be law-abiding? |
| | OBA3 | Do you consider others on campus good cyclists? |

Table 2. Measurement items of parking model

| **Latent variables** | | **Indicators** |
|---|---|---|
| Attitude | AT1 | Do you find parking your bicycle on campus convenient? |
| | AT2 | Do you think the bicycle parking management on campus is adequate? |
| | AT3 | Do you consider the towing mechanism for illegally parked bicycles on campus reasonable? |
| Moral norm | MN1 | Do you consider illegal parking inappropriate? |
| | MN2 | If you see someone illegally parked and didn't get towed, would you park illegally like them? |
| | MN3 | Do you think illegally parked bicycles affect traffic safety? |
| Behavioral intention | BI1 | Do you fully park your bike within the designated parking space? |
| | BI2 | Do you pay attention to whether your parking position might obstruct others from entering or exiting parking spaces? |
| | BI3 | If the remaining space is narrow, would you squeeze your bike tightly between others? |
| Environment perception | EP1 | Do you think there is enough bicycle parking space on campus? |
| | EP2 | Do you think there is enough sheltered parking space on campus to stay away from rain or sun? |
| | EP3 | Do you feel comfortable parking your bike on campus without worrying about damage or theft? |
| Effect of others | EO1 | If someone else's parking obstructs you from retrieving your bike, would you move their bike? |
| | EO2 | If someone else's parking obstructs access, are you indifferent to it and park in a position that blocks access? |
| Self-behavior assessment | SBA1 | Do you think your own parking behavior contributes to a disorderly parking environment on campus? |
| | SBA2 | Do you think your own parking behavior causes inconvenience to others? |
| Others' behavior assessment | OBA1 | Do you think the parking behavior of others on campus contributes to a disorderly parking environment? |
| | OBA2 | Do you think the parking behavior of others on campus causes inconvenience for everyone? |

## 2.2 Data collection

The survey utilized a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree) and was distributed to students, faculty, and staff at National Taiwan University (NTU), the largest university in Taiwan, located in the downtown area of Taipei City. There is intense bicycle usage on the campus, where around 34,000 people inhabit over the area of 110 hectares, and there are more than 25,000 private bicycles, and a bike-sharing system was introduced to contain the number of private bicycles. The heavy reliance on cycling has led to considerable conflicts between cyclists, pedestrians, and other vehicles, and disorderly parked bicycles can be frequently observed on the campus. The survey was anonymously disseminated through social media, and it took approximately 10 minutes to complete. A total of 392 valid responses were collected, with responses from low-frequency cyclists excluded from the analysis. The demographic characteristics of the respondents, including age, gender, educational status, bike ownership, and cycling frequency, are presented in Table 3.

Table 3. Descriptive statistics

| | Freq. | Percent (%) | Cum.percent (%) |
|---|---|---|---|
| **Age** | | | |
| 18-22 | 213 | 54.3 | 54.3 |
| 23-25 | 140 | 35.7 | 90.1 |
| 26-35 | 34 | 8.7 | 98.7 |
| 36-45 | 4 | 1.0 | 99.7 |
| 46-55 | 1 | 0.3 | 100.0 |
| **Gender** | | | |
| Male | 225 | 57.4 | 57.4 |
| Female | 167 | 42.6 | 100.0 |
| **Bike ownership** | | | |
| Yes | 271 | 69.1 | 69.1 |
| No | 121 | 30.9 | 100.0 |
| **Identity** | | | |
| Undergraduate | 238 | 60.7 | 60.7 |
| Graduate | 142 | 36.2 | 96.9 |
| Staff or faculty | 12 | 3.1 | 100.0 |
| **Cycling frequency (days/week)** | | | |
| 0 | 88 | 0 | 88 |
| < 1 | 47 | < 1 | 47 |
| 1-2 | 40 | 1-2 | 40 |
| 3-5 | 97 | 3-5 | 97 |
| 6-7 | 120 | 6-7 | 120 |

A significant portion of the respondents (54.3%) were between the ages of 18-22, while 35.7% were in the 23-25 age range. Only a small percentage (9.9%) were aged 26 or above, indicating that the majority of the participants were young adults. Gender distribution showed that 57.4% of the respondents were male, while 42.6% were female, revealing a relatively balanced gender representation in the study. Regarding educational background, 60.7% of the respondents identified as undergraduates, while 36.2% were graduate students. A small percentage (3.1%) were staff or faculty members. Bike ownership was prevalent among the respondents, with 69.1% reporting that they owned a bike, while 30.9% did not. This suggests that a considerable proportion of participants had personal access to bicycles. The analysis of cycling frequency showed varied engagement levels. About 22.4% of the respondents reported no cycling activity, while 12% cycled less than once per week. Those who cycled 1-2 days per week made up 10.2% of the sample, while 24.7% cycled 3-5 days per week. The highest proportion (30.6%) cycled frequently, in the range of 6-7 days per week, demonstrating a significant level of bicycle usage among participants. Overall, these statistics illustrate that the majority of the respondents were young students, predominantly undergraduates, with a relatively high rate of bike ownership and frequent cycling habits.

### 2.3 Data reliability and validity

To assess the reliability of the survey data, the internal consistency of each construct was examined using Cronbach's alpha (α) correlation test. This metric, which ranges from 0 to 1, indicates the degree of consistency among the items within a construct, with values closer to 1 signifying stronger internal reliability (Nunnally & Bernstein, 1994). Additionally, the validity of the items was analyzed through Confirmatory Factor Analysis (CFA), which tests predefined hypotheses regarding the relationships between items and their respective factors.

### 2.4 Modeling approach

The Structural Equation Modeling (SEM) approach was employed to estimate indirect correlations within the dataset and visually describe the relationships among variables. SEM consists of two components:

- Measurement Model: Assesses the validity and reliability of observed variables through CFA.
- Structural Model: Examines hypothesized relationships between latent constructs.

Model fit was evaluated using various indices, including Chi-square, Root Mean Square Error of Approximation (RMSEA), Comparative Fit Index (CFI), and Standardized Root Mean Square Residual (SRMR).

## 3. RESULTS

### 3.1 Reliability and Validity of the Questionnaire

#### 3.1.1 Riding Model

Before analyzing the structural model, the reliability and validity of each construct were assessed and shown in Table 4. Cronbach's alpha coefficients were used to determine internal consistency, with values ranging from 0.658 to 0.898, demonstrating moderate to high reliability (Zhang et al., 2020). The Cronbach's alpha values of SBA ($\alpha$=0.860), EO ($\alpha$ = 0.864), and OBA ($\alpha$ = 0.898) indicate strong reliability, while constructs like MN ($\alpha$ = 0.658) show moderate reliability. Moreover, the composite reliability (CR) of all constructs ranged from 0.633 to 0.831, meeting the recommended threshold of 0.60 (Hair et al., 2016). CFA was then performed on the sample to validate the measurement model. The standardized factor loadings of each construct were examined, with all items exceeding the recommended minimum threshold of 0.6 (Bagozzi & Yi, 1988), except for MN1 (0.487) and BI4 (0.49), which were slightly lower but still within an acceptable range. The highest loading was for SBA1 (0.92), indicating strong item representation of its latent construct.

Table 4. Reliability, construct reliability of riding model

| Construct | Items | Mean | SD | Standardized loading | Cronbach's α | CR |
|---|---|---|---|---|---|---|
| AT | AT1 | 4.5 | 0.8 | 0.748 | 0.837** | 0.817 |
| | AT2 | | | 0.747 | | |
| | AT3 | | | 0.98 | | |
| MN | MN1 | 4.4 | 0.8 | 0.487 | 0.658* | 0.633 |
| | MN2 | | | 0.71 | | |
| | MN3 | | | 0.767 | | |
| RP | RP1 | 3.6 | 1.1 | 0.678 | 0.751** | 0.705 |
| | RP2 | | | 0.423 | | |
| | RP3 | | | 0.75 | | |
| | RP4 | | | 0.833 | | |
| BI | BI1 | 2.4 | 1.1 | 0.701 | 0.736** | 0.677 |
| | BI2 | | | 0.581 | | |
| | BI3 | | | 0.708 | | |
| | BI4 | | | 0.49 | | |
| | BI5 | | | 0.617 | | |
| EP | EP1 | 3.2 | 1.0 | 0.67 | 0.862** | 0.751 |
| | EP2 | | | 0.561 | | |
| | EP3 | | | 0.823 | | |
| | EP4 | | | 0.811 | | |
| | EP5 | | | 0.743 | | |
| | EP6 | | | 0.474 | | |
| | EP7 | | | 0.52 | | |
| | EP8 | | | 0.757 | | |
| EO | EO1 | 4.1 | 0.9 | 0.844 | 0.864** | 0.845 |
| | EO2 | | | 0.817 | | |
| | EO3 | | | 0.815 | | |
| SBA | SBA1 | 3.9 | 0.7 | 0.869 | 0.860** | 0.824 |
| | SBA2 | | | 0.806 | | |
| | SBA3 | | | 0.782 | | |
| OBA | OBA1 | 3.0 | 0.9 | 0.856 | 0.898** | 0.871 |
| | OBA2 | | | 0.872 | | |
| | OBA3 | | | 0.862 | | |

### 3.1.2 Parking Model

The reliability and validity of the constructs for the parking model were also assessed and shown in Table 5. Cronbach's alpha coefficients were used to measure internal consistency, with values ranging from 0.390 to 0.875, indicating moderate to high reliability (Zhang et al., 2020). The highest reliability was observed for SBA ($\alpha$ = 0.875) and OBA ($\alpha$ = 0.862), confirming their strong internal consistency. However, EO ($\alpha$ = 0.390) showed relatively lower reliability, suggesting potential measurement issues. Other constructs, such as MN ($\alpha$ = 0.607) and AT ($\alpha$ = 0.664), displayed acceptable reliability levels. Additionally, the composite reliability (CR) values ranged from 0.614 to 0.889, meeting the recommended threshold of 0.60 (Hair et al., 2016). CFA was conducted to validate the measurement model. The standardized factor loadings were examined, with most items exceeding the recommended minimum threshold of 0.6 (Bagozzi & Yi, 1988). However, AT3 (0.481) and EO1 (0.33) had lower loadings, indicating weaker representation of their respective constructs. Despite this, SBA1 (0.92) and OBA1 (0.905) showed high factor loadings, emphasizing their strong representation of their latent constructs.

Table 5. Reliability, construct reliability of parking model

| Construct | Items | Mean | SD | Standardized loading | Cronbach's Alpha | CR |
|---|---|---|---|---|---|---|
| AT | AT1 | 3.1 | 1.1 | 0.661 | 0.664* | 0.650 |
| | AT2 | | | 0.791 | | |
| | AT3 | | | 0.481 | | |
| MN | MN1 | 3.6 | 0.9 | 0.709 | 0.607* | 0.666 |
| | MN2 | | | 0.455 | | |
| | MN3 | | | 0.638 | | |
| BI | BI1 | 2.2 | 1.0 | 0.691 | 0.569 | 0.614 |
| | BI2 | | | 0.512 | | |
| | BI3 | | | 0.497 | | |
| EP | EP1 | 2.3 | 1.0 | 0.859 | 0.6677* | 0.689 |
| | EP2 | | | 0.64 | | |
| | EP3 | | | 0.426 | | |
| EO | EO1 | 3.6 | 1.2 | 0.33 | 0.390 | 0.629 |
| | EO2 | | | 0.692 | | |
| SBA | SBA1 | 3.9 | 1.0 | 0.92 | 0.875** | 0.889 |
| | SBA2 | | | 0.847 | | |
| OBA | OBA1 | 2.3 | 0.8 | 0.905 | 0.862** | 0.879 |
| | OBA2 | | | 0.841 | | |

### 3.2 Structural Equation Modeling

#### 3.2.1 Riding Model

A Structural Equation Model (SEM) was developed to examine the relationships between latent constructs in the riding model. The model fit indices are presented in Table 6, indicating an acceptable model fit. The Chi-square divided by degrees of freedom ($\chi^2/df$) is 2.367, falling within the acceptable range ($1 < \chi^2/df$), confirming a good model fit. The Comparative Fit Index (CFI) value of 0.888 is slightly below the 0.90 threshold, while the Tucker-Lewis Index (TLI)= 0.877 also approaches the acceptable level. The Root Mean Square Error of Approximation (RMSEA)= 0.060 and Standardized Root Mean Square Residual (SRMR)= 0.088 meet the recommended standards (< 0.08), confirming that the model sufficiently explains the observed data.

The standardized path coefficients, their standard errors (SEs), critical ratios (C.R.), and p-values are summarized in Table 7 (please also see the path diagram in Appendix A). Several key relationships were identified. Attitude (AT) significantly influenced Behavioral Intention (BI) ($\beta$= 0.514), indicating that a positive attitude toward cycling increases the intention to conduct risky behaviors. Moral Norms (MN) had a strong positive effect on Effect of Others (EO) ($\beta$= 0.952) and Risk Perception (RP) ($\beta$ = 0.889), demonstrating that individuals with strong moral considerations are more likely to be influenced by others and perceive higher risks while cycling. Environmental Perception (EP) was significantly affected by Moral Norms (MN) ($\beta$= −0.314), suggesting that higher moral norms may reduce the perception of external environmental influences. Furthermore, Environmental Perception (EP) significantly impacted Behavioral Intention (BI) ($\beta$ = 0.341), showing that a favorable perception of the riding environment encourages greater behavioral intention. However, Effect of Others (EO) negatively influenced Behavioral Intention (BI) ($\beta$ = −0.455), suggesting that social influences may deter risky cycling behaviors in some cases. Additionally, Assessment of Others' Behavior (OBA) positively influenced Self-Behavior Assessment (SBA) ($\beta$= 0.923), demonstrating that cyclists who critically assess others' riding behaviors tend to be more aware of their own actions.

Table 6. Fit statistics of the models

| **Models** | **Fit indices** | | | | |
|---|---|---|---|---|---|
| | $\chi^2/df$ | **CFI** | **TLI** | **SRMR** | **RMSEA** |
| Standard value | $1 < \chi^2/df < 3$ | > 0.90 | > 0.90 | < 0.080 | < 0.080 |
| Riding model | 2.367 | 0.888 | 0.877 | 0.088 | 0.060 |
| Parking model | 2.679 | 0.899 | 0.847 | 0.067 | 0.072 |

Table 7. Regression weights of the constructs in the riding model

| | | | **Estimate** | **S.E.** | **C.R.** | **P.value** |
|---|---|---|---|---|---|---|
| EP | <--- | AT | 0.226 | 0.077 | 2.920 | .003 |
| EP | <--- | MN | - 0.314 | 0.091 | -3.439 | *** |
| EO | <--- | MN | 0.952 | 0.136 | 7.014 | *** |
| BI | <--- | AT | 0.514 | 0.123 | 4.183 | *** |
| RP | <--- | MN | 0.889 | 0.144 | 6.177 | *** |
| OBA | <--- | EP | 0.630 | 0.070 | 8.999 | *** |
| OBA | <--- | EO | 0.124 | 0.051 | 2.443 | .015 |
| BI | <--- | EP | 0.341 | 0.092 | 3.703 | *** |
| BI | <--- | EO | - 0.455 | 0.084 | -5.381 | *** |
| SBA | <--- | RP | - 0.171 | 0.060 | -2.867 | .004 |
| SBA | <--- | BI | - 0.110 | 0.044 | -2.481 | .013 |
| SBA | <--- | OBA | 0.213 | 0.053 | 4.032 | *** |
| SBA | <--- | MN | 0.498 | 0.124 | 4.017 | *** |

Note: * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.
The path coefficients shown in the table are all standardized path coefficients.

### 3.2.2 Parking Model

A Structural Equation Model (SEM) was developed to analyze the relationships between the latent constructs in the parking model. The model fit indices in Table 6 indicate that the parking model has a reasonable fit. The Chi-square divided by degrees of freedom ($\chi^2/df$) is 2.679, which falls within the acceptable range ($1 < \chi^2/df < 3$), confirming a good model fit. The

Comparative Fit Index (CFI)= 0.899 meets the recommended threshold (>0.90), indicating an acceptable level of fit. However, the Tucker-Lewis Index (TLI)= 0.847 is slightly below the standard value, suggesting moderate model fit. The Root Mean Square Error of Approximation (RMSEA)= 0.072 and Standardized Root Mean Square Residual (SRMR)= 0.067 fall below the acceptable cutoff of 0.08, confirming that the model sufficiently represents the observed data.

The standardized path coefficients, standard errors (SEs), critical ratios (C.R.), and p-values are summarized in Table 8 (please also see the path diagram in Appendix B). Several significant relationships were identified. Attitude (AT) had a significant positive influence on Environmental Perception (EP) ($\beta$= 0.226,), suggesting that individuals with positive attitudes toward cycling perceive the parking environment more favorably. Moral Norms (MN) strongly influenced Risk Perception (RP) ($\beta$ = 0.889) and Effect of Others (EO) ($\beta$= 0.952), demonstrating that individuals with strong moral values are more likely to perceive risk in parking behavior and be influenced by others' actions. However, Moral Norms (MN) negatively affected Environmental Perception (EP) ($\beta$= − 0.314), indicating that cyclists who prioritize moral norms may perceive the parking environment more critically. In terms of behavioral relationships, Environmental Perception (EP) significantly influenced Behavioral Intention (BI) ($\beta$= 0.341), meaning that a positive parking environment enhances the intention to park bicycles improperly. Conversely, Effect of Others (EO) negatively impacted Behavioral Intention (BI) ($\beta$=− 0.455), indicating that external social influences might encourage individuals from engaging in proper parking behavior. Self-Behavior Assessment (SBA) was positively influenced by Assessment of Others' Behavior (OBA) ($\beta$= 0.923), suggesting that cyclists who evaluate others' parking behavior critically are more likely to assess their own behavior as well.

Table 8. Regression weights of the constructs in the parking model

| | | | Estimate | S.E. | C.R. | P.value |
|---|---|---|---|---|---|---|
| EP | <--- | AT | 0.455 | 0.072 | 6.345 | *** |
| EO | <--- | AT | - 0.197 | 0.065 | -3.024 | 0.002 |
| EO | <--- | MN | 0.776 | 0.113 | 6.874 | *** |
| OBA | <--- | EP | 0.522 | 0.117 | 4.461 | *** |
| OBA | <--- | EP | 0.522 | 0.117 | 4.461 | *** |
| OBA | <--- | EO | - 0.291 | 0.080 | -3.637 | *** |
| SBA | <--- | EO | 0.715 | 0.150 | 4.779 | *** |
| SBA | <--- | BI | - 0.216 | 0.106 | -2.032 | 0.042 |
| SBA | <--- | OBA | 0.320 | 0.076 | 4.236 | *** |

Note: * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.
The path coefficients shown in the table are all standardized path coefficients.

### 3.3 Comprehensive discussion

The results of riding and parking models confirm the hypothesized relationships, highlighting the importance of attitudes, moral norms, and environmental perception in shaping cycling behavior. The estimation results indicate that self-perception plays a critical role in shaping cyclists' behavioral intention. Individuals with higher self-assessment scores tend to exhibit stronger intention to follow cycling norms. Moreover, moral norms significantly influence both self-assessment and the assessment of others' behavior, suggesting that ethical considerations are central to cycling behavior. Risk perception negatively affects behavioral intention, indicating that cyclists who perceive higher risks are less likely to engage in certain cycling behaviors. The impact of others' behavior on cyclists' decisions also underscores the importance of social influences in urban cycling dynamics. These results suggest that policies aimed at improving cycling behavior need to consider enhancing self-awareness, reinforcing moral norms, and mitigating risk perception through better infrastructure and education campaigns.

## 4. CONCLUDING REMARKS

### 4.1 Conclusions

This study explored cyclist behavior by analyzing the perception of self and others through Structural Equation Modeling (SEM) based on the Theory of Planned Behavior (TPB). The results indicate that attitudes, moral norms, risk perception, and environmental perception significantly influence behavioral intentions, self-assessment, and the evaluation of others' behaviors. The riding model highlights that positive attitudes and environmental perceptions enhance behavioral intention, while social influences can negatively impact cycling decisions. Similarly, the parking model confirms that environmental factors and social norms shape parking behaviors, with external social influences sometimes leading to improper parking practices. These findings emphasize the complex interplay between psychological, social, and environmental factors, underscoring the need for improved cycling infrastructure, awareness campaigns, and policy interventions to foster a safer and more sustainable cycling environment and culture.

### 4.2 Limitations

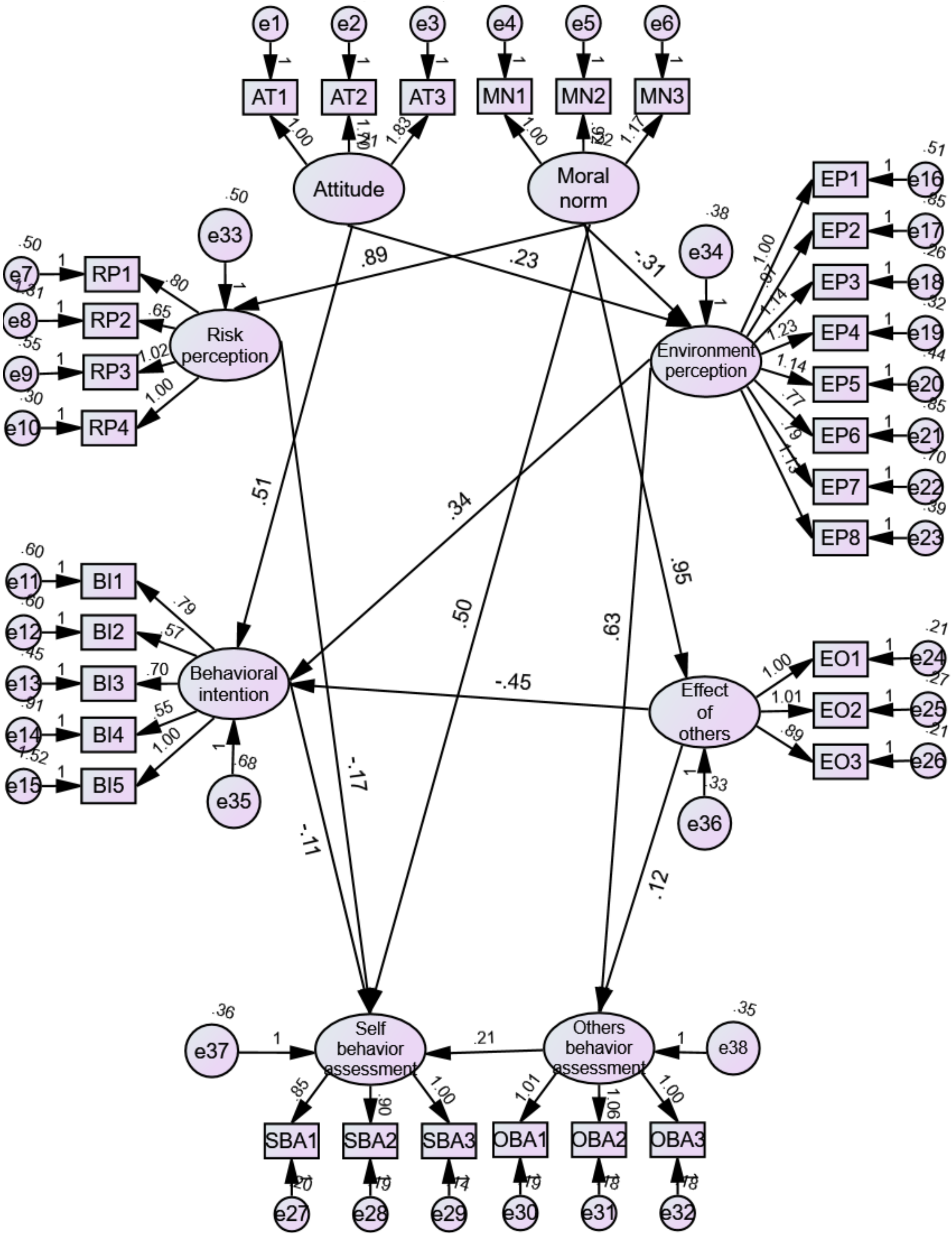
Despite the research findings concluded above, this study has several limits that need to be acknowledged. First, the sample is drawn from National Taiwan University (NTU), which constrains the generalizability of findings to broader populations with different cycling habits and environments. Second, the use of cross-sectional data restricts the ability to establish causal relationships, necessitating longitudinal research for further insights. Third, measurement limits, such as lower reliability in some constructs, highlight the need for refined survey items and mixed-method approaches. Additionally, external factors like weather, policy enforcement, and road conditions were not directly considered, potentially affecting behavioral outcomes. Lastly, reliance on self-reported data may introduce response biases, suggesting that future research should incorporate objective measures like GPS tracking and observational studies to validate the findings.

### 4.3 Future work

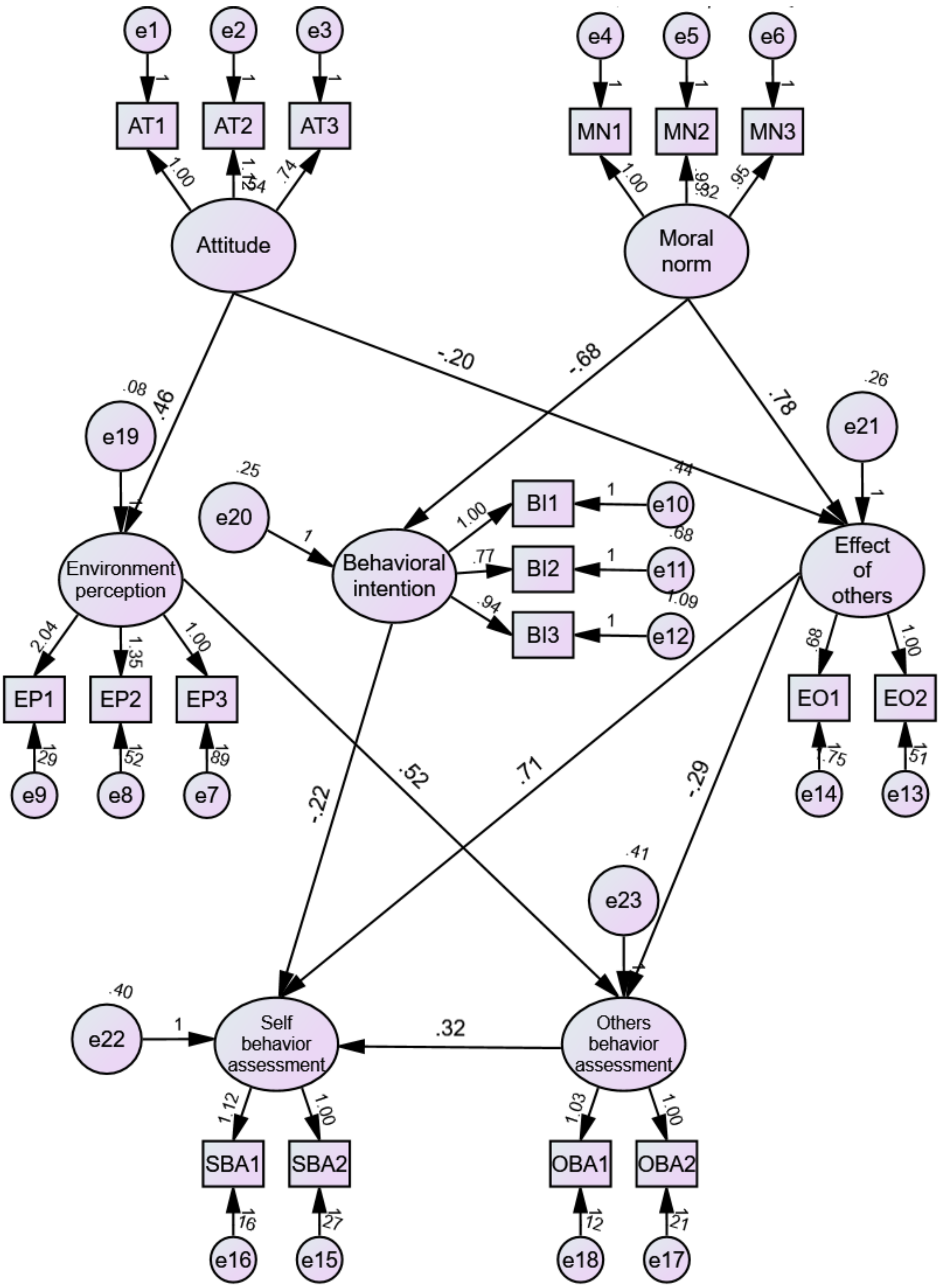
Future studies may be planned to expand the research scope to include diverse geographical contexts beyond university settings, as cycling cultures and infrastructure vary significantly across different cities and countries. Longitudinal studies should be conducted to track behavioral changes over time, allowing for more detailed understanding of the effects of policy interventions and environmental modifications. Incorporating real-world data through GPS tracking, video surveillance, and experimental studies can enhance the accuracy of behavioral assessments. Furthermore, investigating the role of digital technologies, such as bike-sharing systems and cycling apps, could provide insights into how technological advancements influence cycling behavior. Finally, future research should focus on evaluating the effectiveness of policy interventions, including education programs, law enforcement measures, and urban planning strategies, to promote safer and more responsible cycling behavior.

## APPENDICES

Appendix A. Path diagram of the riding model



Appendix B. Path diagram of the parking model

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