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碩士論文

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Master's Thesis

基於自我及他人感知的單車行為分析：以國立臺灣大學為例

Cyclist Behavior Analysis on the Perception of Self and Others: A Case Study of National Taiwan University

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中文摘要

自行車是一種可持續的城市交通方式，但基礎設施不足迫使騎士與車輛和行人共享道路，增加了衝突和安全隱憂。本研究基於擴展的計劃行為理論（The Theory of Planned Behavior）框架，運用結構方程模型（Structural Equation Modeling）探討心理因素如何影響騎士的認知和行為。關鍵因素包括態度、道德規範、風險認知、環境認知、他人影響、行為意圖、自我行為評估以及對他人行為的評估。

本研究在國立臺灣大學進行問卷調查，該校園內超過 25,000 輛私人自行車服務將近 4,0000 人，橫跨 110 公頃的校園面積，導致騎士、行人和其他車輛之間產生相當大的衝突，校園內經常可見違規停放的自行車以及單車騎士的事故，由此可見單車管理為校園重要課題之一，因此本研究分別建立騎乘行為和停車行為模型，以捕捉各行為類型的不同心理機制，希望藉此對於校園單車管理提供建議。

SEM 結果顯示模型具有優異的適配度（騎乘：CFI = 0.921；停車：CFI = 0.926），並揭示正向態度矛盾地增加危險行為意圖($\beta = 0.245$)，而社會意識則起強烈的嚇阻作用($\beta = -0.332$)。道德規範在兩個模型中都是影響風險認知和社會敏感性的核心構念。研究提供實證證據顯示自利偏誤的存在，即騎士在意圖從事不當行為的同時，仍保持對其不當性的認知。研究結果強調需要同儕教育計畫、道德規範提升策略、平衡的基礎設施設計，以及整合性干預框架，以促進更安全的騎乘環境，讓自我覺察和規範的騎乘文化能夠解決潛在的行為問題。

關鍵字：騎乘行為、計劃行為理論、結構方程模型、自我認知、社會比較、大學校園

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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 an extended Theory of Planned Behavior (TPB) framework. Key factors include attitudes, moral norms, risk perception, environmental perception, effect of others, behavioral intention, self-behavior assessment, and assessment of others' behavior.

A questionnaire survey was conducted at National Taiwan University (NTU), where over 25,000 private bicycles serve around 40,000 people across 110 hectares, leading to considerable conflicts between cyclists, pedestrians, and other vehicles, with disorderly parked bicycles frequently observed on campus. The study developed separate models for riding and parking behaviors to capture distinct psychological mechanisms governing each behavior type.

The SEM results demonstrate excellent model fit (riding: CFI = 0.921; parking: CFI = 0.926) and reveal that positive attitudes paradoxically increase risky behavioral intentions ($\beta = 0.245$), while social awareness serves as a strong deterrent ($\beta = -0.332$). Moral norms emerge as central constructs influencing risk perception and social sensitivity across both models. The study provides empirical evidence for self-serving biases where cyclists retain awareness of inappropriate behaviors while intending to perform them. The findings highlight the need for peer education programs, moral norm activation strategies, balanced infrastructure design, and integrated intervention frameworks to promote safer cycling environments where self-aware and regulated

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cycling culture addresses underlying behavioral issues.

Keywords: Cycling behavior, Theory of Planned Behavior, Structural equation modeling, Self-perception, Social comparison, University campus

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Chapter 1 Introduction

1.1 Study background

1.1.1 Cycling in urban transportation

Cycling is identified as a key dimension of a sustainable urban mobility culture and receiving more and more attention. As cities deal with the problems of fast urbanization and climate disruption, riding bicycles is recognized as a cleaner, more sustainable alternative to four-wheeled transport (Pucher & Buehler, 2008). Environmentally, cycling is a pollution-free mode of transportation that plays a direct part in the reduction of greenhouse gas emissions and the improvement in air quality - important issues in most highly populated cities. Economically, bicycles use little infrastructure and urban space, which makes them much more cost effective than most sustainable developments. From the perspective of public health, cycling is beneficial for active living, reduces the burden of non-communicable diseases, and has been related to better mental health outcomes as a result of an increased level of physical activity and less stress (Oja et al., 2011).

Further, cycling can be an efficient remedy to increasing traffic congestion and sub-optimal land use in urban centers. Bicycles are a fraction of the size of cars — when they're moving, as well as when they're parked — making them perfect for crowded cities that are in short supply of road and parking space (Shaheen et al., 2010). Moreover, bicycles are necessary to fill in short-trip needs, for example, campuses are areas that are relatively isolated but also extensive, so they need an efficient, versatile, and clean transport. Bicycles are heavily used by students, faculty, and staff in traveling throughout the spacious campus (Balsas, 2003). The highly walkable characteristic makes it an ideal environment for cycling, but without proper infrastructure, cycling takes up too much

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space, leading to traffic jams, crashes and conflict among users with varying modes of transportation. With the more bikes out there, the more problem or conflicts will be brought about. Plenty of cities have inadequate dedicated bicycle lanes, and cyclists often share the road with cars or ride on the sidewalk with pedestrians. This co-existing area causes conflicts and risky situation particularly in regions where traffic regulations are loosely observed. Also, lack of secured parking compounds problems from chaotic bicycle parking and theft, making the bicycle trip less appealing and convenient (Larsen & El-Geneidy, 2011).

Psychosocial and cultural factors also significantly determine the adoption of cycling. The acceptance of the bicycle is affected to large extent by attitudes towards cycling, social norms, risk perceptions, and also the image of bicycle infrastructure (Heinen et al., 2011). Differences in cultural perception of cycling, in terms of being a lower-status necessity, or higher-status lifestyle choice, also influence its uptake. Thus, cultivating a strong cycling culture usually demands some shifts in behavior and also in society. In other words, urban cycling is both the problem and the solution. This promotion needs to be addressed in an overall educational approach, including infrastructure building, reforms to laws and regulations, behavior change programs, continuously monitoring usage patterns and safety records. And as cities work to be more livable, equitable, and sustainable, bikes will no doubt remain an important cornerstone to future mobility systems.

1.1.2 The study of positive and risky cycling behavior

The behavioral aspects of cycling have frequently been considered in terms of safety and the psychology of risk-taking on a bicycle. For urban traffic, good habits such as following traffic rules, respecting pedestrians, and parking in designated zones are striven-for. On the other hand, acts such as running red lights, cycling against traffic, or

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parking outside designated areas are safety risks and therefore lower public support for cycling (Johnson et al., 2014). In order to understand how cyclists behave, we have to look at the full range of the decisions cyclists make.

Previous research has typically examined cycling-safety behavior, estimated in terms of risk-taking behavior, and the extent to which actions contribute to or inhibit the likelihood of accident involvement (Chaurand & Delhomme, 2013). This kind of research fields is helpful, but it hardly comes close to doing justice to the multifarious behaviors that such a categorization system typifies. “Good cycling behavior” is a variety of acts which show concern for safety, legality, and community. These rules include respecting traffic lights, reining in your speed in heavy-traffic areas, using designated bike lanes if they exist, making hand gestures when making turns, giving pedestrians the right-of-way, and parking your bike where it belongs (not blocking sidewalks or doors). But those are not just expressions of personal caution: they are more expressions of a city pool in which cyclists-more or less-work together to share space with other road users. At the other extreme, dangerous cycling behavior poses formidable challenges to urban mobility. Skipping lights, cutting the corner, not riding on cycle paths and not wearing a helmet add up to paint cyclists in a bad light. Not only do these actions endanger cyclists they have negative, domino-like consequences effect on pedestrians and other cyclists that can even undermine public support for bike infrastructure investments (Walker et al., 2014).

What is interesting about studying cycling behavior is that an individual often switches between pro and risky behavior even during a single journey. A cyclist may strictly adhere to the rules of the road on arterial roads and local streets, but ride through a pedestrian mall or square as a time and space saving cut through or park their bike responsibly every day except when you are late and it’s just so convenient to leave it in

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an inappropriate place. This discrepancy in behavior indicates that cycling decisions may be just as influenced by situational factors as by deep-seated attitudes and values. Several determinants of such behaviors have been identified by previous work. Time constraints, quality of infrastructure, visibility of enforcement, weather, and social norms, for example, can influence whether a safer or riskier action is selected by a cyclist in a given context. A lot of this research has, however, been restricted to individual decision making processes and appears to have ignored the social and comparative aspects of cycling behavior.

1.1.3 Perception of self and others

It is also important to note that the distinguishing factor of this research is the self-perception and social comparison processes of cyclists. How cyclists perceive their behavior (e.g., as safe or law-abiding) influences not only their own intentions but also their response to the behavior of others. Conversely, perceived others' risky or responsible cycling behavior feeds back, through its influence on second-person beliefs, onto one's own behavior, leading to a feedback loop that is rooted in social cognition (Fruhen & Flin, 2015). One of the most interesting and yet under researched areas of cyclist behavior is that of how cyclists compare themselves to others. This work also acknowledges that decisions to cycle take place in a social environment where people observe, interpret and react to what others do when they cycle.

Cyclists' self-perception and behavior have multiple levels. At the personal level, cyclists construct perceptions of themselves as “responsible” or “risk-taking” riders from prior behaviors, values, and social identities. A cyclist that identifies as safety conscious experiences cognitive dissonance if they engage in unsafe behavior, which motivates them to stop performing the unsafe behavior or change the definition of what is to be safe." The cyclist who frames themselves as twice into rule-bending may simply feel

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they're standing up against what people would call unfair. These self-views continue to be molded and remolded by social comparison processes. If cyclists see fellow riders breaking the law, running the red light or parking where they're not supposed to, they may recalibrate their propriety. The phenomenon, called the influence of descriptive norm, means that how people perceive what is "normal" in terms of cycling behavior has a huge impact on their decision making that risky behavior looks very common and harmless. If more people are living life on the edge and seemingly getting away with it, then other people will start to edge closer toward the edge, on the assumption that it's no problem at all. The inverse is also important; there is an obvious reason why cyclists' perception of what others are doing impacts how they perceive and justify their own actions. Let's say a cyclist goes through red lights sometimes, he or she may consider other cyclists way worse than they are as a way to protect their own self-image, asserting they're not as bad as the others even when they're riding just as dangerously. This self-serving bias in social comparison allows individuals to reinforce their position as responsible cyclists.

Moreover, the visibility of various behaviors yields amusing perceptual illusions. They look dramatic and draw attention to themselves and may be overrepresented in the mind of cyclists about what constitutes "normal" cycling behavior. Meanwhile, the tens of thousands of examples of people cycling around areas safely is forgotten, producing a distorted image where one thinks that risk in in much larger numbers than it really is. That feedback loop of self- and social reflection is what we can think of as a "behavioral feedback loop." Personal actions affect group norms, which in turn affect individual perceptions and behavior (Kormos et al., 2015). An awareness of this loop is important for designing successful interventions to encourage safer cycling behavior, since it suggests that changing individual attitudes may be inadequate if the wider social context

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actively endorses unsafe behavior. The implications of these processes are not only felt in terms of the safety of the individual but also in relation to how the cycling culture is encountered in the wider community. It is more likely for cyclists to practice cycling responsibly when members of the community they belonged to practice such knows when they are socially reinforced. At the other end of the spectrum, in environments where libertine behavior is normalized, the social spends may compel safety-conscious people to make riskier decisions.

1.2 Research objectives

In response to the growing complexity of cyclist behavior in urban settings, this study aims to achieve the following objectives:

1. To explore the psychological and environmental determinants of cycling behavior, including both riding and parking practices, using the Theory of Planned Behavior (TPB) as the foundational framework.
2. To analyze the interplay between self-perception and social perception in shaping behavioral intention and risk evaluation among cyclists.
3. To construct a comprehensive Structural Equation Model (SEM) that integrates variables such as attitude, moral norm, environmental perception, effect of others, and so on to know better about the causation relationship between the latent constructs regarding the cycling behavior.

1.3 Thesis organization

As illustrated in Fig. 1-1, the organization of the thesis includes the following sections. Chapter 1 includes the introduction of the study background and the research objectives of the thesis. In this chapter, the main issues addressed in this thesis are discussed. Chapter 2 consists of the literature review that is relevant to cycling behavior, riding and parking

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behavior, theory of planned behavior and perception of self and others. The research about factors outside the TPB model are included in this chapter. The problem statement and the research framework are organized in Chapter 3 that identifies what this research aims to investigate. Hypotheses are provided for further examination, and it includes the questionnaire design, data collection and structural equation modeling. After that, Chapter 4 indicates how the model is proceeded, in which it contains descriptive statistics, factor analysis, model specification and estimation results. This chapter also talks about the discussion of the results of riding and parking. Last but not least, the final chapter shows concluding remarks. It includes the conclusion, limitations and future work of the study. Insights based on the results of the model and the implication are provided to improve bike management in the near future.

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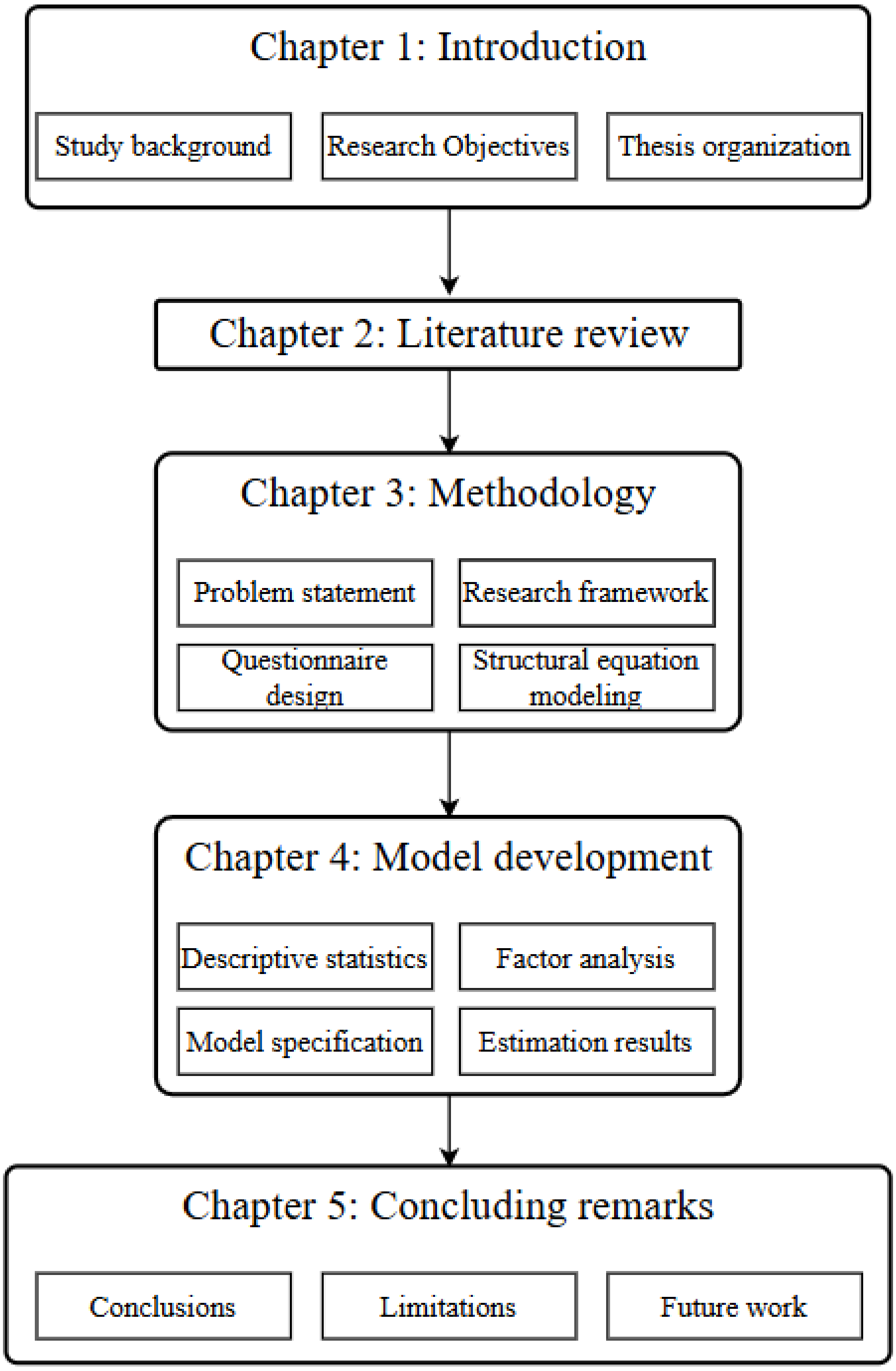

Fig. 1-1 Thesis organization

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Chapter 2 Literature Review

In recent years, the widening consideration of active transport and sustainable urban transport has brought bicycle use into greater academic focus. Whereas early studies focused on mode or route choice, more recent research has turned to finer points, such as how cyclists behave — the way in which they ride, where they park, and the psychological and physical environment that leads to such actions. It is critical to understand these behaviors both for the promotion of safe and responsible cycling, and to ensure that infrastructural and policy objectives are in agreement with real-world practices. Therefore, this paper investigates the behavioral factors that influence cycling, and draws upon behavior theoretical models, and new extensions which conceptualize the role of perceived risk, environmental context, and social influence. The objective is to get a better grasp of what affects cycling and how this knowledge can help create safer, more inviting urban and university environments.

2.1 Cycling behavior

2.1.1 Riding behavior

An individual chooses to ride a bike for various reasons, including personal habits, intentional safety behaviors, and the surrounding environmental conditions. Instead of thinking of cyclists as one homogenous group, recent research has focused on how cycling clusters based on age, purpose of trip, social norms, and local context. The most frequent issues found in the literature is the impact of security and perceived risk. Cyclists' behavior changes depending on how safe they feel. Indeed, to take an example, a number of authors (Dozza et al., 2016; Goldenbeld et al., 2012) have reported that attentional distractions, including mobile phone use and listening to music while cycling heighten risk levels and diminish situational awareness. They are most common among

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younger riders and associated with lower use of helmets and a greater number of violations of traffic regulations.

Environmental issues also become a major factor. Across studies, the presence and quality of cycling infrastructure, including separated cycling lanes, well-designed intersections and evenness of road surfaces, has been consistently shown to correlate with higher-order compliance and positive cycling behavior (Chevalier et al., 2019; Larsen et al., 2016). But infrastructure is not enough on its own. Bad designs, like narrow bike lanes or misunderstanding signs, can make conflict with pedestrians or drivers worse.

In university campuses and bike-sharing cities, the literature shows the positive effect of distance to key locations, such as schools, business districts, or transit stations, on the cycling frequency (Scott & Ciuro, 2019; Zhou et al., 2012). Curiously, some studies indicate that weather and time-of-day are a more influential factor of cycling patterns than density of infrastructure alone (Scott & Ciuro, 2019). In addition, behavior is also influenced by social factors and norms. Cyclists who witness other people breaking rules such as improperly riding on sidewalks may be more likely to break rules in turn. This “broken windows” effect underscores the importance of perceived surveillance, social cues, and a sense of shared responsibility in maintaining a positive cycling culture (Useche et al., 2022).

Briefly, riding is therefore best understood as the result of individual decisions influenced by infrastructure, perceived safety and social context. The most effective interventions aim to address all three dimensions — through education, smart infrastructure design, and community involvement.

2.1.2 Parking behavior

Bike parking may not feel as crucial as riding, but it is a surprisingly significant

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factor in how people see and use bikes in cities (Aldred et al., 2017). As dockless shared bikes have proliferated, parking behavior has become an issue of concern in urban planning, particularly in places where improperly parked bikes can impede the sidewalk or pose a safety concern. A consistent theme in all this research is that unregulated or inadequate car storage fosters disorder. Shared bikes have been dropped off around town haphazardly not because their users are thoughtless, but simply because there aren't enough practical, explicit places to park (Chevalier et al., 2019; Useche et al., 2022). There is a lack of knowledge, or ambiguous rules, that help create this situation. The existence of infrastructure is not sufficient. How well it is designed and where it's located matters. Parking areas located near building entrances, transit stops or dense walking flows, however, are subject to much higher compliance. Vertical racks or visible boundaries designs increased the orderliness (Chevalier et al., 2019).

Once again, the social norms are very strong. People are more likely to park their bike neatly when they see others do the same. From the other side, if disorder is apparent and there is no enforcement, the norm becomes rule breaking (Cialdini & Goldstein, 2004). That's been true in the university environments, and in the densely- populated urban setting. Some cities and companies have tried solutions such as incentive systems — rewarding people for parking correct or penalizing bad behavior. Those systems sound promising but work only when they're accompanied by infrastructure and education (Wang et al., 2021).

Ultimately, better parking behavior is about more than just adding more racks. It takes a multifaceted solution: better design, smarter policy, and a culture of shared responsibility. When these elements come together, cities can develop environments where bike parking are convenient and civil for all.

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2.2 The theory of planned behavior

The Theory of Planned Behavior (TPB) proposed by Icek Ajzen (1991) has become one of the most widely used models in the social and behavioral sciences related to the prediction and explanation of human action. Based on Fishbein and Ajzen's (1975) preceding Theory of Reasoned Action (TRA) model, TPB consists of three primary elements – attitude toward the behavior, subjective norms, and perceived behavioral control. Together these factors form the behavioral intention, which is regarded as the most proximal determinant of the behavior itself. It has since become one of the most commonly used models, especially in studies of voluntary behaviors like travel choices, health promoting behaviors and environmental behaviors. TPB at its fundamental level suggests that human action is driven by three types of reasons: behavioral beliefs (attitude toward the behavior), normative beliefs (subjective norms) and control beliefs (perceived behavioral control). These all combine to form an individual's behavioral intentions which lastly serve as the predictor to actual behavior.

In transport studies, the TPB has been used to explore aspects of travel mode choice by individuals, for example cycling. Numerous studies have employed TPB to explain cycling behavior, particularly for adolescents and young adults. Wu et al. (2023) investigated Chinese adolescents' cycling with regard to TPB showing that attitudes and perceived behavioral control had main effects on cycling intentions. In addition, Liu et al. (2023) elaborated TPB by adding other variables including environmental concern and proved that TPB variables are robust predictors of cycling behavior. Structural Equation Modeling (SEM) has been widely used to further substantiate and quantify the inter-relations between the TPB constructs. This is a statistical analysis method to test the causal and indirect relation among latent variables. By using SEM along with TPB,

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research have revealed effects of attitudes, moderate effects of perceived behavioral control and small effects of subjective norms on behavioral intentions (Zhou et al., 2012; Li et al., 2021).

In addition, SEM provides flexibility and potential to link and examine with the TPB extended models with other variables such as habit (Liu et al., 2023), environmental risk, or emotional responses (Lu et al., 2022), as well evidencing TPB's robustness. These results support the use of TPB as a theoretical model and guidance in intervention planning for safe and sustainable cycling.

2.3 Additional factors

Although the TPB has been useful to understand cycling intentions and behaviors, several authors have extended their approach incorporating other psychological constructs that represent decision processes in everyday life. Among them, risk perception is one of the most popular extensions studied. Also, how people perceive their own cycling and the cycling of others, are also important. These variables enable researchers to not only grasp what individuals plan to do, but also how they judge safety and responsibility in a complex traffic situation.

2.3.1 Risk perception

Risk perception is the judgment made by a person about the likelihood of a risk and the magnitude of the potential harm. In cycling, it changes the way you feel safe and actually make decisions, whether that is about speed, about positioning, about wearing a helmet or not. Unlike objective risk, which can be quantified using crash rate statistics, perceived risk is psychological and varies widely across individuals. This notion is particularly relevant for cyclists, who are exposed road users and must contend with dynamic environments.

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Lehtonen et al. (2016) reported that experienced cyclists were more cautious and more prompt in their reactions to perceived hazards compared to less experienced cyclists when filming video clips of urban cycling environment. These discrepancies indicate that experience is likely to influence the perception of a risk and overall detection of a hazard. Recently the literature has come to consider the risk perception as a latent variable in the SEM-based behavioral models. For example, Bi, Hui, et al. (2023) included risk perception in their TPB-SEM model on food delivery cyclists, and they reported that risk perception played a significant mediating part between safety attitudes and risk-taking. Likewise, risk perception has been examined in relation to variables such as sensation seeking and self-efficacy for the purpose of explaining deviant bicycle behavior (Zhang et al., 2023).

The experience of risk is not only of psychological interest for individual safety but also a constructed reality used to model cycling behavior. Its incorporation in traffic conflict prediction models within SEM considers both theoretical implications and practical advises of policy and infrastructure recommendations to mitigate traffic conflicts and promote safe cycling behavior.

2.3.2 Environmental perception

Environmental perception relates to the behavior of cyclists' perceptions and responses to physical and situational stimuli from his or her environment. This includes visibility and design of the environment (e.g., bike lanes and crossings), perceived auditory cues (e.g., the sound of a car or a warning), and the overall detection of the surroundings in traffic. In contrast to the objective aspects of the environment, perception is a phenomenon that is subjective and influenced by life experiences, strategies of attention and levels of consciousness.

A number of studies have shown that cyclists do not passively interpret information

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from the environment but use adaptive visual and auditory strategies to integrate themselves into traffic. Ahlstrom et al. (2016) demonstrated that the cyclists accessing smartphones relied on the spare visual capacity during distraction conditions to keep detection of critical traffic condition even in the presence of a secondary task. The study finds cyclists tend to avoid known hazardous sites more for the self-initiated task, while glancing more toward the cycle track and the surrounding road before task engagement. This can imply self-regulated environment that is based on perception of complexity and risk.

More generally in the literature, SEM has recently introduced a latent construct of environmental perception, which impacts on both intention and behavior. For instance, Liu et al. (2021) demonstrated that environmental satisfaction which included satisfaction with noise levels, lighting, visibility and traffic safety—significantly explained the prediction of adolescents' intention to cycle in urban settings. These results support the idea that not only physical infrastructure but also the perception of cycling conditions influence cycling behavior on the basis of constantly being interpreted as safe and convenient.

2.3.3 Effect of others

Another important aspect in the understanding of cycling behavior, is the influence of others' presence and actions, social pressure, or direct interactions in shared traffic spaces. These effects go beyond the subjective norms of the TPB and reflect how cyclists make sense of, respond to and occasionally mimic or reject the behaviors of others, which indicates that cyclists are heavily determined of the perception of other road users.

Basford et al. (2002) found variations in cyclists' behavior, including speed, placement, and rule following, in response to the observed behavior of pedestrians and motor vehicles in their proximity. For instance, a cyclist would often be more defensive

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or cautious due to the presence of aggressive or inattentive drivers. Even more interesting is how cyclists, in some cases, attribute blame for traffic tension or conflict to others. Gamble et al. (2016) found that cyclists often justified their own risky or illegal behaviors by pointing to the actions of others. This attribution scheme provides an example of how interpersonal dynamics on the road influence riders perception of safety and entitlement.

In addition, the imitation of social behavior is an important component of social cycling. When riding in packs, cyclists often follow the lead of the group, legal or not, either because of constraints to cohesiveness or because of a version of the bystander effect. These tensions are especially apparent in student-centric locations, such as university towns, and on campus where the culture of cycling can be influenced by peer visibility and norms. More recently, the application of SEM has also started examining others' behavior as a latent variable that influences cyclists' intentions. For example, Wang et al. (2021) showed that peers' behavior influenced the actual use of risky and safety-related cycling behaviors by young cyclists.

In summary, the actions of others, observation, face-to-face encounters and cultural interpretation create a psychological background against which cyclists choose their behavior. Knowledge of this factor provides more in-depth understanding of community-level interventions to encourage safe, respectful traffic behavior.

2.4 Summary

This chapter has provided an overview of the factors in cycling behavior, particularly with regard to riding and parking—two key areas of opportunity for urban and campus accessibility that have been largely absent from conventional transportation research. Studies had shown that how people ride is influenced by infrastructure, perceptions of safety and social norms, and that the choices people made about where to park are

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informed by a mix of design, enforcement and cultural factors. Both are intricately embedded in the experience of the users and the cyclists' daily lives to enhance convenience and order.

Additionally, the Theory of Planned Behavior (TPB) is viewed a base for behavior driven by intention. Several researchers have successfully used TPB, especially in conjunction with SEM, to determine how attitudes, norms and perceived control influence the behavior of cycling. This model has been expanded by including other parameters that make the model more realistic. These include psychological considerations such as risk perception, environmental interpretation, and social concern. However, despite these extensions, most existing studies have overlooked the critical role of social comparison processes and how cyclists' self-perception interacts with their evaluation of others' behaviors in shaping cycling decisions. On top of that, this research includes the addition of self-behavior and others' behavior assessments, which provides even more detail on how internal contemplation and external observations contribute to preferences.

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Chapter 3 Methodology

3.1 Problem statement

Urban cycling has become a crucial part of sustainable urban transport systems providing environmental and health benefits as well as solving urban congestion issues. However, the fast-growing use of bicycles has brought about the complexity of behavioral dynamics greatly influencing cycling safety and the effectiveness of cycling facilities. At the National Taiwan University (NTU) campus, there are over 25,000 private bicycles serving around 40,000 people in the 110ha campus area, resulting in an upsurge of cycling conflicts among cyclists, pedestrians, and other vehicle users. Chaotic parking behavior often blocks pedestrian routes and poses risks to road safety as Fig. 3-1. The real issue is coming to terms with the psychological mechanisms through which cyclists are motivated, specifically how people perceive and judge their own behavior and the behavior of others. This lack of knowledge restricts the efficacy of interventions to encourage safer cycling.

Fig. 3-1 Parking chaos around NTU campus (Source: Po-Sen Huang)

Moreover, previous research has mainly focused on cycling behavior through separate factors rather than full models capturing associations among attitudes, social influences, environment perceptions and behavior. This study fills these gaps by

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examining how psychological constructs grounded in the Theory of Planned Behavior (TPB) influence cycling and parking behaviors and by zeroing in on the comparing effects of the judgement of one's behavior to that of others on intentions. Characterizing these forces is important to craft informed policies to improve the safety and responsibility of urban cycling.

3.2 Research framework

The research framework is shown in Fig. 3-2. The study adopts a comprehensive behavioral analysis approach based on the extended Theory of Planned Behavior (TPB) framework to examine cycling behavior in university settings. The framework integrates psychological, social, and environmental factors to understand how cyclists' self-perception and social comparison processes influence their riding and parking behaviors. The research process begins with questionnaire design incorporating eight key constructs: attitude, moral norms, risk perception, environmental perception, effect of others, behavioral intention, self-behavior assessment, and assessment of others' behavior. The questionnaire items were developed based on established TPB literature and adapted specifically for cycling behavior contexts, using 5-point Likert scales to capture attitudinal and perceptual measures.

Data collection was conducted at National Taiwan University (NTU), where intense bicycle usage creates a natural laboratory for studying cycling behavior dynamics. The survey was distributed to students, faculty, and staff through social media platforms, targeting individuals with varying cycling frequencies and demographic characteristics. A total of 399 valid responses were collected after excluding low-frequency cyclists from the analysis.

The analytical framework employs a two-model approach, recognizing that riding

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behavior and parking behavior are governed by different psychological mechanisms and environmental factors. The riding behavior model focuses on understanding risky cycling intentions and safety-related decision-making processes, while the parking behavior model examines compliance with parking regulations and social dynamics surrounding parking decisions.

Structural Equation Modeling (SEM) is utilized as the primary analytical method to validate the measurement instruments and test hypothesized relationships among latent constructs. The SEM analysis follows a two-stage approach: first, Confirmatory Factor Analysis (CFA) is conducted to assess the reliability and validity of the measurement model; second, structural path analysis is performed to examine the relationships between constructs and test the proposed hypotheses.

Then, the model incorporates demographic variables including age, gender, educational status, bike ownership, and cycling frequency to examine individual differences in behavioral patterns. These variables are tested for their effects on the latent constructs to provide insights into how personal characteristics influence cycling behavior. Model evaluation is conducted using multiple fit indices including Chi-square statistics, Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR). The results are interpreted to identify significant relationships and provide recommendations for improving cycling safety and infrastructure management.

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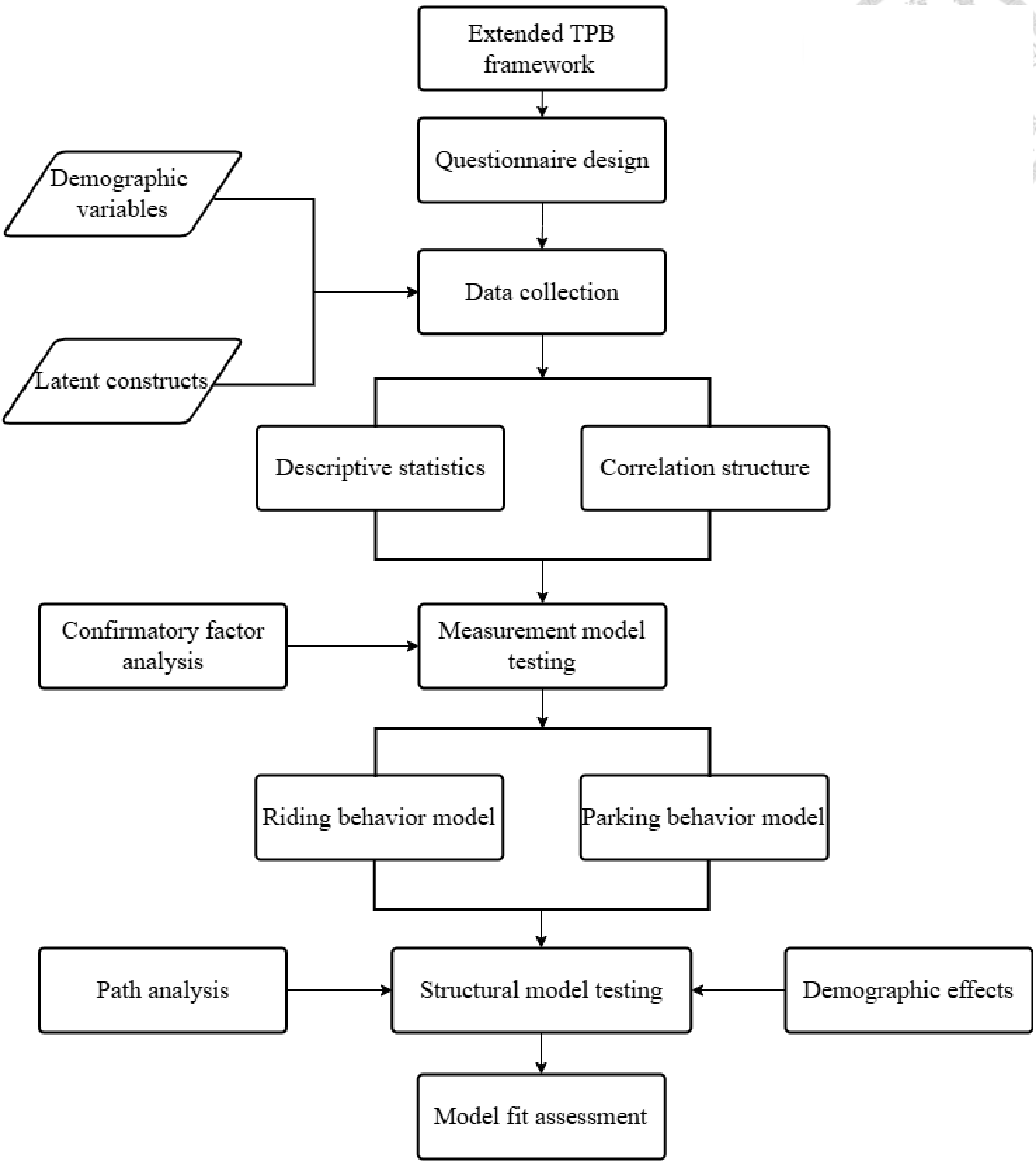

Fig. 3-2 Research framework

3.3 Factors

3.3.1 Attitude

Attitude is the sum of individual's cognitive and affective outcome to perform a certain cycling behavior. Attitude in the context of this research refers to the level of favorableness or un-favorableness of engaging in a given riding or parking behavior. For the riding status, attitude concerns self-evaluation about the need, frequency and

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preference for cycling in the campus. This involves an evaluation of cycling as a transport mode, individual cycling behavior and university cycling particularities. The attitudes condition reflects personal predispositions that can affect risk-taking behaviors and adherence to cycling norms.

In the parking model, attitude as an element refers to evaluations of parking convenience, management systems and regulatory mechanisms. Such opinions may relate to the adequacy of parking facilities, satisfaction with existing parking arrangements and attitudes toward enforcement policies, such as bicycle towing regulations. Attitudes of residents in the parking infrastructure and management are predicted to affect environmental perceptions and compliance behavior. Attitude is measured using attitudinal items that directly measure personal beliefs and preferences regarding biking and parking behaviors, thus shedding light on the motivational orientations underlying intentions.

3.3.2 Moral norms

Moral norms refer to a person's own internal moral values and ethical standards for cycling. In contrast to subjective norms, which refer to perceived social expectations, moral norms represent one's personal moral obligations that lead to behavior even in the absence of external social pressure. Within the context of the ride moral norms involve attitudes about appropriate speed, safe following, and concern for others' safety. These may reflect personal norms concerning behaviors that can pose risks to others, aligning with internalized beliefs about responsible cycling practices.

Regarding parking, moral norms are beliefs about what constitutes good parking practice, upholding the proper use of spaces. The moral norms framework is especially salient to university settings where informal social contracts and community norms exert a great deal of influence over individual behaviors. Indeed, strong moral norms may act

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as an internal regulator, such that behavior is maintained even in the absence of formal enforcement of traffic and parking rules.

3.3.3 Risk perception

Perceived risk is the degree of danger, harm or negativity each individual thinks of potential hazards of bicycle use. This construct measures the subjective assessments of bicycle safety threats and susceptibility of campus cycling environments to accidents or injuries. Risk perception in the riding model would include fears of having a collision with a pedestrian, vehicle, or another cyclist, or an accident due to insufficient cycling skills or environmental forces. Such evaluations would involve considerations of crossing hazards and design risks that can affect behavioral decisions. The factor risk perception is assessed on the basis of items that investigate the level of concern toward different categories of bicycle accidents and environmental threats. There are individual differences in these perceptions that may be critical in shaping intentions. Principally, higher levels of risk perception about cycling's activity may be positively related to risk-averse cycling behaviors and compliance with safety norms.

3.3.4 Environmental perception

Environmental perception refers to the personal perceptions of the physical environment and living conditions favoring bicycle use. The factor measures subjective evaluations of the environmental quality, its capacity and their user-friendliness, and it is based on the user's perspective. For the riding model, environmental perception concerns the safety, comfort and suitability of on-campus cycling infrastructures. This includes analysis of such variables as quality of cycle lane design, adequacy of lighting, number of deceleration facilities and whether roads are designed with cyclists in mind.

In the parking model, the consideration of the environment focuses on parking

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facility suitability, such as space availability, presence of shelter facilities, and security. Environmental perception plays a vital role in connecting objective environmental situations with subjective behaviors, as behavioral choices are not only depending on objective environments but also on individuals' perceptions of this environment.

3.3.5 Behavioral intention

Behavioral intention is an expression of the probability that people will perform certain cycling or parking behaviors. Behavioral intention, as the primary criterion variable in the TPB framework, represents the direct precursor of behavior and specifies the motivational factors contributing to the choice of behavior. In the riding model, behavioral intention refers to the intentions to engage in different risk behaviors such as riding with no hands, riding side-by-side, using mobiles while cycling, carrying passengers or using an umbrella while riding.

For parking behaviors, behavioral intention states to use space appropriately, respect other people's access and adhere to parking regulations. Behavioral intention is regarded as an immediate antecedent of behavior, bridging the gap between a person's attitudes and norms, and psychological determinants outlined in the extended TPB.

3.3.6 Effect of others

Effect of others reflects the impact of the actions executed by other cyclists on an individual-level decision-making procedure. This model includes mechanisms of social learning and conformity that lead to influence in the behavioral decision making by observing and imitating others. Within the riding model, the effect of others refers to how an individual's behavior is influenced by observing others, whether through witnessing dangerous riding, accidents, or positive examples of safe cycling.

In case of parking behavior, effect of others examines what it means to react to

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observed parking transgressions, access obstructions and chaotic parking patterns such as double and triple parking. The impact of others recognizes that decisions to self-control are made in the context of social influence and led by the behaviors of others. It may act as a mediator for transmitting social norms and the behavior culture to be maintained or modified.

3.3.7 Self-behavior assessment

Self-behavior assessment reflects one's own cycling and parking attitudes, including perceptions of self-compliance, safety and appropriateness of conduct. This self-witnessing includes self-judging and self-evaluative processes that influence future behavior. Perceptions related to a person's riding safety adherence of road rules and cycling ability are included in the riding model.

In the context of parking behavior, self-behavior assessment pertains to the perceptions of one's own role in the condition of parking order, the extent to which one considers the rights of the others in order to establish parking order, and the level to which one adheres to the rules pertaining to parking. Self-behavior assessment which is based on moral norm, risk perception, and behavioral intention is some forms of self-regulation that functions as proposition about the coherence of people's behavior and adherence to the norm.

3.3.8 Assessment of others' behavior

Assessment of others' behavior is a measure of individuals' appraisals of the behavior of other cyclists, including how safe, rule-following and appropriate other cyclists are judged to be. This construct reflects social comparison and community norms that affect individual norms and expectations. Assessment of others applies to safe and legal courses of action of other cyclists and motor vehicle operators on campus.

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With respect to parking behavior, other-referenced judgments refer to judgments of others with respect to community parking behavior, conceptualized as perceptions of the general behavior of others. Judgment of others' behavior can influence personal behavioral standards through social comparison processes but also through the comparison of own to others' behavior, which can highlight discrepancies between self-judgments and judgment of others, offering insights into self-serving biases or normative behavior of the community.

3.4 Hypotheses

3.4.1 Riding model

Based on the Theory of Planned Behavior and existing literature on behavior, the following hypotheses are proposed and the hypothesized riding structural model is showed as Fig. 3-3:

H1a: Positive attitudes toward cycling significantly increase behavioral intention.

H1b: Moral norms significantly increase cyclists' risk perception.

H1c: Moral norms positively influence the effect of others on individual cycling decisions.

H1d: Moral norms negatively influence how cyclists perceive the environment.

H1e: Environmental perception significantly increases behavioral intention.

H1f: The effect of others negatively influences behavioral intention.

H1g: Environmental perception positively influences assessment of others' behavior.

H1h: The effect of others positively influences assessment of others' behavior.

H1i: Risk perception negatively influences self-behavior assessment.

H1j: Behavioral intention negatively influences self-behavior assessment.

H1k: Assessment of others' behavior positively influences self-behavior assessment.

H1l: Moral norms positively influence self-behavior assessment.

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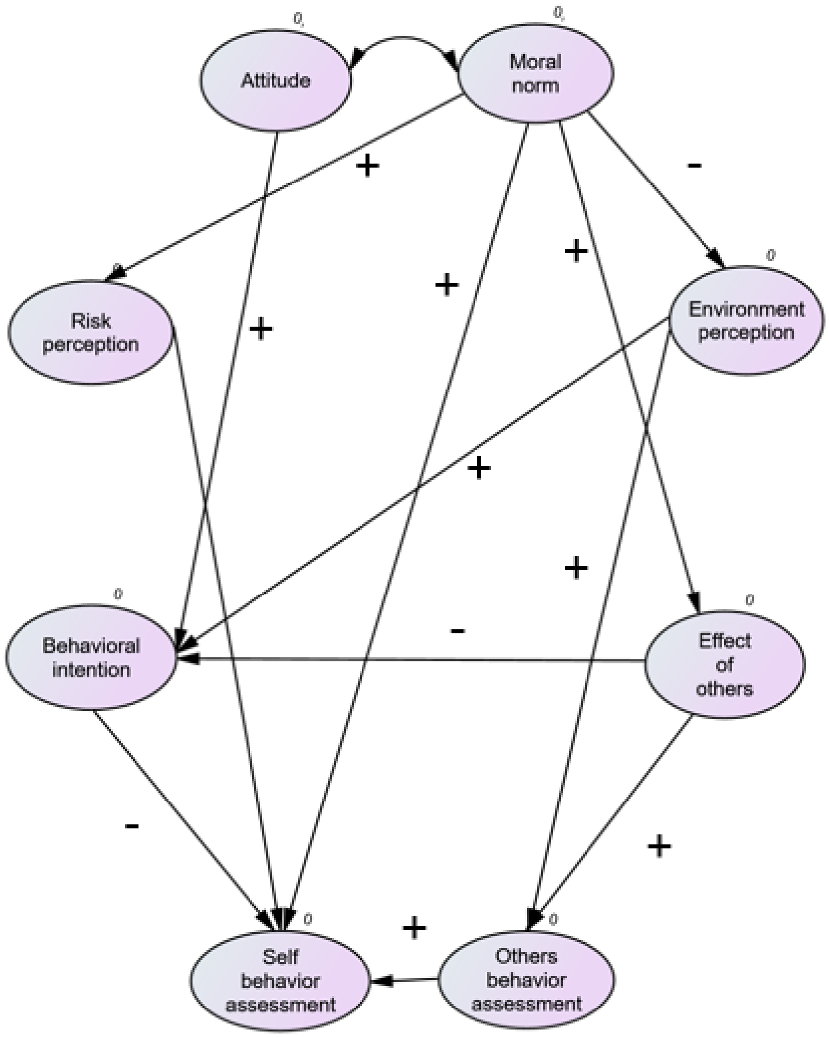

Fig. 3-3 Hypothesized riding structural model

3.4.2 Parking model

Based on the Theory of Planned Behavior and existing literature on parking behavior, the following hypotheses are proposed and the hypothesized parking structural model is showed as Fig. 3-4:

H2a: Attitudes toward parking positively influence environmental perception.

H2b: Attitudes negatively influence the effect of others.

H2c: Moral norms positively influence the effect of others.

H2d: Moral norms negatively influence the behavioral intention

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H2e: Environmental perception increases assessment of others' parking behavior.

H2f: Effect of others negatively influences assessment of others' parking behavior.

H2g: Effect of others positively influences self-behavior assessment.

H2h: Behavioral intention negatively influences self-behavior assessment.

H2i: Assessment of others' parking behavior positively influences self-behavior assessment.

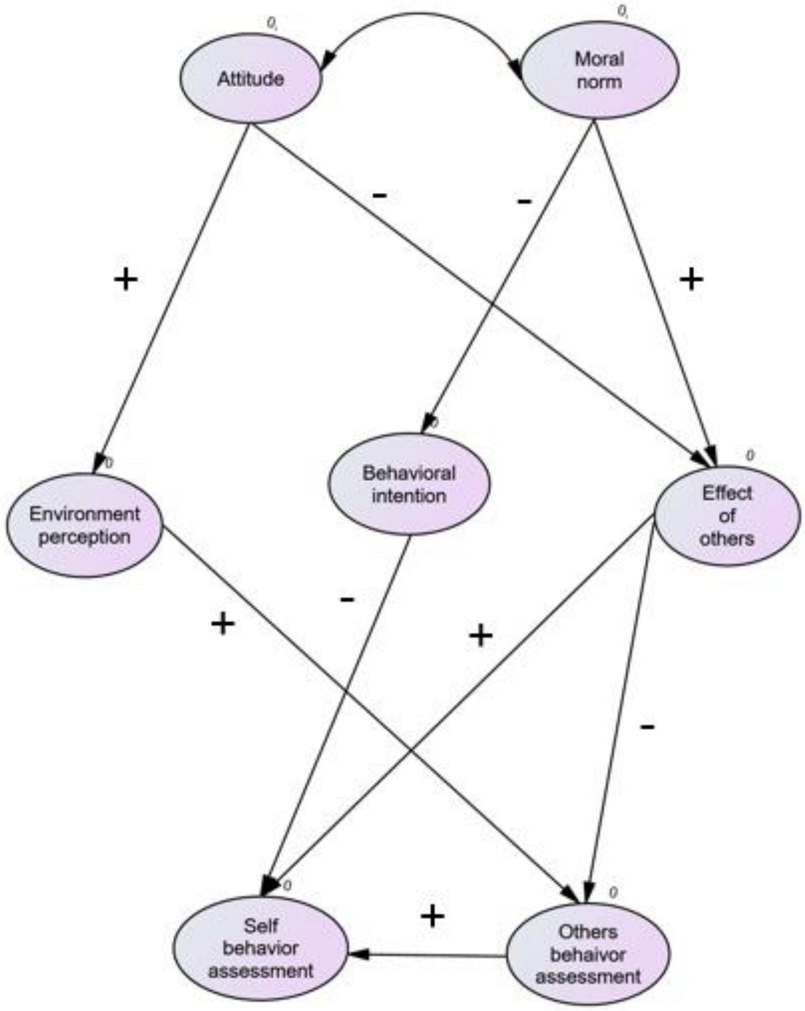

Fig. 3-4 Hypothesized parking structural model

3.5 Questionnaire design

A structured questionnaire was developed to collect data on demographic

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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). To capture potential framing effects in self versus others' evaluations, two versions of the questionnaire (Version A and Version B) were designed with reversed question sequences regarding self-behavior assessment and assessment of others' behavior. These versions were randomly distributed to participants to examine whether the order of asking about self-evaluation versus others' evaluation influenced response patterns. The measurement items of riding and parking models are shown in Table 3-1 and Table 3-2.

Table 3-1 Measurement items of riding model

Latent variables		**Indicators**	**Mean**	**S.D.**
Attitude	AT1	Do you think you have the need to ride a bicycle on campus?	4.68	0.59
	AT2	Do you often ride a bicycle?	4.28	1.01
	AT3	Do you often ride a bicycle on campus?	4.52	0.81
Moral norm	MN1	Do you consider speeding inappropriate?	4.02	0.97
	MN2	Do you consider maintaining safe distance appropriate?	4.63	0.62
	MN3	If your riding behavior can endanger others, would you avoid such behavior?	4.49	0.73
Risk perception	RP1	Are you concerned about collisions with pedestrians or cars?	4.13	0.96

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	RP2	Are you concerned about accidents due to lack of riding skills?	2.91	1.27
	RP3	Do you think the road layout poses a danger?	3.39	1.12
	RP4	Do you think the geometry of intersections poses a danger?	4.01	0.99
Behavioral intention	BI1	Do you ever take your hands off the handlebars?	2.37	1.08
	BI2	Do you ever ride side by side with another cyclist?	2.53	0.94
	BI3	Do you ever use your phone while riding?	2.04	0.96
	BI4	Do you ever carry a passenger on your bicycle?	1.88	1.09
	BI5	Do you ride with an umbrella when it's raining?	3.31	1.55
Environment perception	EP1	Do you find it safe to ride a bicycle on campus?	3.42	0.96
	EP2	Does riding a bicycle on campus make you feel pressured?	2.65	1.11
	EP3	Do you think the riding environment on campus is friendly?	3.42	0.87
	EP4	Do you find the road environment on campus comfortable?	3.38	0.96
	EP5	Do you think the bike lane planning on campus is adequate?	2.96	0.98
	EP6	Do you think the campus lighting is sufficient?	2.99	1.05
	EP7	Do you think the campus has adequate deceleration facilities for bikes?	2.77	0.98
	EP8	Do you think the road design on campus is friendly to bicycle riding?	3.19	0.95
Effect of	EO1	If you see others engaging in dangerous riding	4.05	0.86

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others		behavior, would you avoid similar riding behaviors?		
	EO2	If you witness cases of riding accidents, would you therefore avoid similar riding behaviors?	4.12	0.91
	EO3	Do you try to follow good riding behavior demonstrated by others as much as possible?	4.15	0.80
Self-behavior assessment	SBA1	Do you consider your riding behavior safe?	3.99	0.73
	SBA2	Do you consider your riding behavior law-abiding?	3.95	0.75
	SBA3	Do you consider yourself a good cyclist?	3.93	0.78
Assessment of others' behavior	OBA1	Do you consider the riding behavior of others on campus to be safe?	4.68	0.59
	OBA2	Do you consider the riding behavior of others on campus to be law-abiding?	4.28	1.01
	OBA3	Do you consider others on campus good cyclists?	4.52	0.81

Table 3-2 Measurement items of parking model

Latent variables		**Indicators**	**Mean***	**S.D.**
Attitude	AT1	Do you find parking your bicycle on campus convenient?	3.07	1.11
	AT2	Do you think the bicycle parking management on campus is adequate?	2.81	1.04
	AT3	Do you consider the towing mechanism for illegally parked bicycles on campus reasonable?	3.39	1.13
Moral norm	MN1	Do you consider illegal parking inappropriate?	4.10	0.82

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	MN2	If you see someone illegally parked and didn't get towed, would you park illegally like them?	2.63	1.24
	MN3	Do you think illegally parked bicycles affect traffic safety?	3.85	0.83
Behavioral intention	BI1	Do you fully park your bike within the designated parking space?	2.08	0.92
	BI2	Do you pay attention to whether your parking position may obstruct others from entering or exiting parking spaces?	2.01	0.96
	BI3	If the remaining space is narrow, would you squeeze your bike tightly between others?	2.63	1.21
Environment perception	EP1	Do you think there is enough bicycle parking space on campus?	2.45	1.05
	EP2	Do you think there is enough sheltered parking space on campus to stay away from rain or sun?	1.89	0.95
	EP3	Do you feel comfortable parking your bike on campus without worrying about damage or theft?	2.67	1.05
Effect of others	EO1	If someone else's parking obstructs you from retrieving your bike, would you move their bike?	2.91	1.39
	EO2	If someone else's parking obstructs access, are you indifferent to it and park in a position that blocks access?	4.28	0.99
Self-behavior assessment	SBA1	Do you think your own parking behavior contributes to a disorderly parking environment on campus?	3.80	1.02

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	SBA2	Do you think your own parking behavior causes inconvenience to others?	3.91	0.99
Others' behavior assessment	OBA1	Do you think the parking behavior of others on campus contributes to a disorderly parking environment?	2.29	0.82
	OBA2	Do you think the parking behavior of others on campus causes inconvenience for everyone?	2.38	0.86

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). There is intense bicycle usage on the campus, where around 40,000 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 399 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.

3.6 Structural equation modeling

Structural Equation Modeling (SEM) is a comprehensive statistical technique that allows researchers to examine complex relationships among observed and latent variables while accounting for measurement error (Bentler, 1980). As noted by Bentler (1981), the development of latent variable causal models represents the convergence of relatively

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independent research traditions in psychometrics, econometrics, and biometrics, pulling together many already-familiar techniques into one broad framework. SEM integrates factor analysis concepts with simultaneous equation modeling to test theoretical causal structures, providing a powerful tool for theory testing and causal inference (Fassinger, 1987). A complete SEM consists of two fundamental components: the structural model and the measurement model (Jöreskog & Sörbom, 1984). The structural model specifies hypothesized causal relationships among latent variables, while the measurement model defines the relationships between latent variables and their observed indicators (Bollen et al., 2022).

3.6.1 Measurement model

The measurement model consists of two equations that link the latent variables to their observed indicators (Fassinger, 1987):

$$Y = \alpha y + \Lambda y \eta + \varepsilon \tag{3-1}$$

$$X = \alpha x + \Lambda x \xi + \delta \tag{3-2}$$

Where:

- Y and X are vectors of observed indicators for endogenous and exogenous latent variables, respectively
- αy and αx are intercept vectors for the measurement equations
- Λy and Λx are matrices of factor loadings linking latent variables to their indicators
- ε and δ are vectors of measurement errors for y and x indicators

3.6.2 Structural model

The structural model, representing the relationships among latent variables, is expressed using the LISREL notation as (Jöreskog, 1973):

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$$\eta = \alpha\eta + \beta\eta + \Gamma\xi + \zeta \quad (3\text{-}3)$$

Where:

- η is a vector of latent endogenous variables
- $\alpha\eta$ is a vector of intercept terms for the structural equations
- β is a matrix of regression coefficients representing effects of latent endogenous variables on each other
- Γ is a coefficient matrix representing effects of latent exogenous variables (ξ) on latent endogenous variables
- ξ is a vector of latent exogenous variables
- ζ is a vector of structural disturbances

3.6.3 Model assumption

The SEM framework requires several key assumptions (Bentler, 1980; Jöreskog & Sörbom, 1984):

1. **Independence assumptions:**
   - $E(\zeta) = 0$ (structural disturbances have zero mean)
   - $E(\varepsilon) = 0$ and $E(\delta) = 0$ (measurement errors have zero mean)
   - $Cov(\xi, \zeta) = 0$ (exogenous variables are uncorrelated with structural disturbances)
2. **Invertibility assumption:**
   - $(I - \beta)$is invertible, ensuring a unique solution exists

3.6.4 Covariance structure

The model-implied covariance matrix $\sum(\theta)$ is derived from the structural and measurement model parameters. For the general case, the implied covariance matrix can be partitioned as (Bollen et al., 2022):

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$$\sum(\theta) = [\sum_{yy}(\theta)\sum_{yx}(\theta)][\sum_{xy}(\theta)\sum_{xx}(\theta)] \tag{3-4}$$

Where the submatrices are:

$$\sum_{xx}(\theta) = \Lambda x\Phi\Lambda x' + \Theta\delta \tag{3-5}$$

$$\sum_{xy}(\theta) = \Lambda x\Phi\Gamma'(I-\beta)^{-1}\Lambda y \tag{3-6}$$

$$\sum_{yy}(\theta) = \Lambda y(I-\beta)^{-1}(\Gamma\Phi\Gamma' + \Psi)(I-\beta)^{-1}\Lambda y' + \Theta\varepsilon \tag{3-7}$$

Where:

- Φ is the covariance matrix of exogenous latent variables ξ
- Ψ is the covariance matrix of structural disturbances ζ
- $\Theta\varepsilon$ and $\Theta\delta$ are the covariance matrices of measurement errors

3.6.5 Model estimation and identification

Model identification is a prerequisite for parameter estimation, ensuring that unique parameter values can be obtained from the observed covariance matrix (Bollen, 1989). A model is identified when there exists a unique set of parameter values that satisfy the implied moment equations for a specific model structure.

Maximum likelihood (ML) estimation is the dominant approach in SEM, where parameter estimates are obtained by minimizing the discrepancy between the sample covariance matrix S and the model-implied covariance matrix $\sum(\theta)$ (Jöreskog & Sörbom, 1984). The ML fitting function is:

$$F_{ML} = \ln\left|\sum(\theta)\right| - \ln|S| + tr[\Sigma^{-1}(\theta)S] - p$$
$$+\big(\bar{z}-\mu(\theta)\big)'\Sigma^{-1}(\theta)(\bar{z}-\mu(\theta)) \tag{3-8}$$

Where:

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- S is the sample covariance matrix
- $\bar{z}$ is the sample mean vector
- $\mu(\theta)$ is the model-implied mean vector
- p is the number of observed variables

3.6.6 Model Fit Assessment

Model fit is evaluated through multiple indices that assess different aspects of model adequacy (Bentler & Bonett, 1980). The chi-square test statistic provides an overall test of model fit:

$$\chi^2 = (N-1)F_{ML} \tag{3-9}$$

Where N is the sample size. However, due to the sensitivity of the chi-square test to sample size and its tendency to reject models with minor misspecifications in large samples, additional fit indices are commonly employed (Bentler, 1990; Hu & Bentler, 1999).

The **Comparative Fit Index (CFI)** compares the proposed model to a baseline independence model (Bentler, 1990):

$$CFI = 1 - max[\,(\chi_t^2 - df_t),((\chi_\beta^2 - df_\beta),0] \tag{3-10}$$

The Tucker-Lewis Index (TLI), also known as the Non-Normed Fit Index (NNFI), is expressed as (Tucker & Lewis, 1973):

$$TLI = [\left(\chi_\beta^2 \big/ df_\beta\right) - \left(\chi_t^2 \big/ df_t\right)] \Big/ [(\chi_\beta^2 - df_\beta) - 1] \tag{3-11}$$

Where:

- χ_t^2 is the chi-square for the target model
- df_t are the degrees of freedom for the target model
- χ_β^2 is the chi-square for the baseline model
- df_β are the degrees of freedom for the baseline model

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The **Root Mean Square Error of Approximation (RMSEA)** assesses model approximation quality (Steiger, 1980):

$$RMSEA = \sqrt{[max\{(\chi^2 - df)/(df(N-1)), 0\}]} \tag{3-12}$$

The **Standardized Root Mean Square Residual (SRMR)** examines the standardized residuals (Bentler, 1995):

$$SRMR = \sqrt{\left\{2\sum_{i=1}^{P}\sum_{j=1}^{i}[(s_{ij} - \bar{\sigma}_{ij})/(s_{ii}s_{jj})]^2\right\}/p(p+1)} \tag{3-13}$$

Where:

- p is the number of observed variables
- s_{ij} are the observed covariances
- $\bar{\sigma}_{ij}$ are the reproduced covariances
- s_{ii}, s_{jj} are the observed standard deviation

Where s_{ij} are elements of the sample covariance matrix S, $\bar{\sigma}_{ij}$ are elements of the model-implied covariance matrix $\sum(\theta)$, and p is the number of observed variables.

3.6.7 Fit index interpretation

Following conventional guidelines, acceptable model fit is indicated by CFI and TLI values ≥ 0.90 (preferably ≥ 0.95), RMSEA values ≤ 0.08 (preferably ≤ 0.06), and SRMR values ≤ 0.08 (Hu & Bentler, 1999; Bentler, 1990). However, as noted by Marsh et al. (2004), these cutoff values should be interpreted with caution as their performance can vary based on model characteristics, sample size, and other research conditions.

This comprehensive framework allows researchers to test complex theoretical models while simultaneously addressing measurement issues, making SEM particularly valuable for examining relationships among abstract constructs in social and behavioral sciences (Fassinger, 1987). The availability of multiple fit indices enables researchers to

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assess model adequacy from different perspectives, providing a more robust evaluation of model-data correspondence than relying solely on the chi-square test statistic

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Chapter 4 Model Development

In this chapter, the proposed structural equation models and their parameter estimation based on the empirical data collected from the study area, National Taiwan University, are introduced. Based on the constructs identified in Chapter 3, this research will set out to describe how the SEM models were measured, and validate them through empirical testing. Descriptive statistics of the sample are presented at the beginning of the chapter to gain some insights into the sociodemographic and cycling behavior of the respondents.

After that, two separate models are built and validated, the riding behavior model and the parking behavior model. Both models are subjected to a thorough analysis covering factor analysis, model specification, estimation results and discussion. The use of the structural equation modeling technique facilitates dual testing of the various paths, controlling for measurement error, and thus produces strong tests of the theoretical model. Based on systematic analysis of the two models, we hope to identify important psychological predictors for cycling and parking behavior, to examine the effectiveness of the augmented TPB model, and to provide empirical evidence on the basis of which policy recommendations can be made to enhance the campus cycling culture and management of the infrastructure for cycling.

4.1 Descriptive statistics

The descriptive statistics are illustrated in Table 4-1. A significant portion of the respondents (53.92%) were between the ages of 18-22, while 35.70% were in the 23-25 age range. Only a small percentage (10.38%) were aged 26 or above, indicating that the majority of the participants were young adults. Gender distribution showed that 58.23% of the respondents were male, while 41.77% were female, revealing a relatively balanced

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gender representation in the study. Regarding educational background, 60.76% of the respondents were identified as undergraduates, while 35.70% were graduate students. A small percentage (3.54%) were staff or faculty members. Bike ownership was prevalent among the respondents, with 69.11% reporting that they owned a bike, while 30.89% 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 1.00% of the respondents reported no cycling activity, while 4.76% cycled less than once per week. Those who cycled 1-2 days per week made up 18.55% of the sample, while 60.65% cycled 3-5 days per week. The highest proportion (15.04%) 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.

Table 4-1 Descriptive statistics

	Freq.	**Percent (%)**	**Cum. percent (%)**
Age			
18-22	213	53.92	53.92
23-25	141	35.70	89.62
26-35	34	8.61	98.23
>35	7	1.77	100.00
Gender			
Male	230	58.23	58.23
Female	165	41.77	100.00
Bike ownership			
Yes	273	69.11	69.11

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No	122	30.89	100.00
Identity			
Undergraduate	240	60.76	60.76
Graduate	141	35.70	96.46
Staff or faculty	14	3.54	100.00
Cycling frequency (days/week)			
0	4	1.00	1.00
< 1	19	4.76	5.76
1-2	74	18.55	24.31
3-5	242	60.65	84.96
6-7	60	15.04	100.00

4.2 Riding behavior model

A psychological and environmental model of risky riding intentions on campus was analyzed. The model of risky riding behaviors examines psychological and environmental determinants of university cyclists' intentions to engage in risky riding behaviors on campus. This model is developed to understand some of the decision-making processes that lead to potentially risky cycling behavior such as careless cycling. The model includes all the eight constructs from the extended Theory of Planning Behavior model, and explores how attitude, moral norms, risk perception, environmental perception, the effect of others and behavioral intention interact with riding behavior.

Furthermore, the model considers the links between self-behavior assessment and assessment of others' behavior, which allows us to understand how cyclists think about their own actions compared to the perceived behavior of other cyclists. The better

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understanding of these relationships is important for the development of targeted interventions aimed at promoting safe cycling and reducing risky behavior that can result in accidents or conflicts with pedestrians and other road users on campus.

4.2.1 Correlation matrix

Based on the analysis of 399respondents, the correlation matrix Fig. 4-1 shows the relationships between all measured variables in the riding behavior model. The correlations range from weak to strong, with most construct indicators showing appropriate within-construct correlations and expected between-construct relationships. Some key findings are as follows:

1. Attitude indicators (AT1, AT2, AT3) show strong intercorrelations ($r > 0.60$)
2. Moral norm indicators demonstrate moderate correlations ($r = 0.40\text{-}0.70$)
3. Risk perception items show varied correlations, with RP4 showing strongest relationships
4. Behavioral intention indicators display moderate intercorrelations
5. Environmental perception items show consistent moderate to strong correlations
6. Effect of others indicators demonstrate strong relationships ($r > 0.70$)
7. Self-behavior assessment items show very strong correlations ($r > 0.80$)
8. Assessment of other’s behavior indicators exhibit strong correlations ($r > 0.85$)

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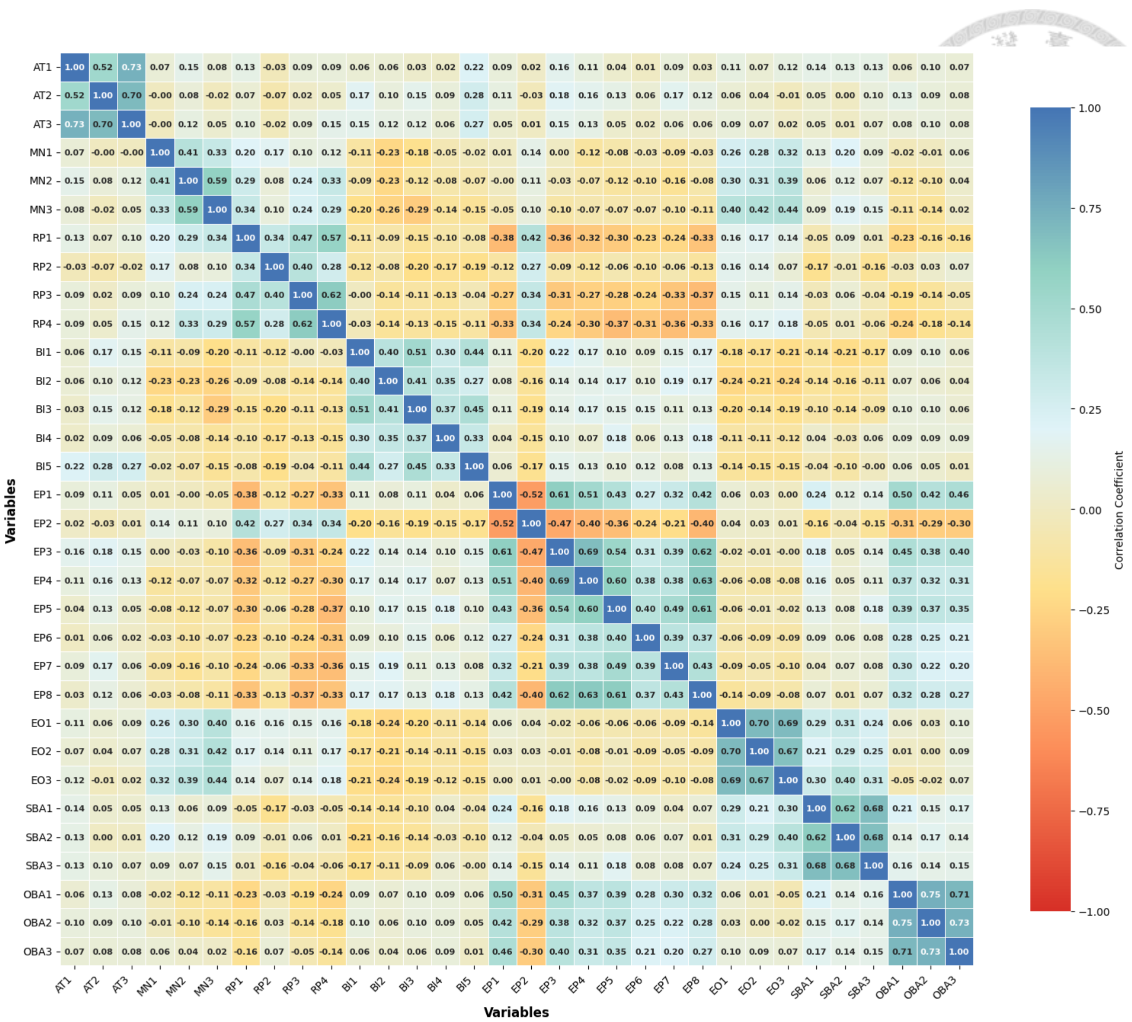

Fig. 4-1 Correlation matrix of riding model

4.2.2 Factor analysis

Before proceeding to structural model analysis, the reliability and validity of each construct were evaluated, as summarized in Table 4-2. Internal consistency was assessed using Cronbach's alpha, with values ranging from 0.668 to 0.898, indicating acceptable to high reliability (Taber, 2020). Constructs such as SBA (α = 0.853), EO (α = 0.866), and OBA (α = 0.890) demonstrated strong internal consistency, whereas MN (α = 0.668) reflected moderate reliability. In addition, composite reliability (CR) values across all constructs ranged from 0.571 to 0.871, exceeding the recommended threshold of 0.60 (Hair et al., 2016), further supporting the internal consistency of the measurement model.

Confirmatory Factor Analysis (CFA) was conducted to assess the validity of the

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measurement model. Most standardized factor loadings surpassed the recommended minimum of 0.6 (Bagozzi & Yi, 1988), confirming adequate indicator reliability. However, a few items such as MN1 (0.426), BI2 (0.500), and BI4 (0.463) fell slightly below the threshold, though still within a tolerable range. Notably, items like AT3 (0.823) and OBA2 (0.802) exhibited the highest loadings, reflecting strong representation of their respective latent constructs.

Table 4-2 Reliability, construct reliability of riding behavior model

Construct	**Items**	**Mean**	**SD**	**Standardized loading**	**Cronbach's α**	**CR**
AT	AT1	4.49	0.7	0.735	0.823**	0.797
	AT2			0.698		
	AT3			0.823		
MN	MN1	4.38	0.61	0.426	0.668	0.571
	MN2			0.633		
	MN3			0.597		
RP	RP1	3.61	0.82	0.605	0.749*	0.699
	RP2			0.435		
	RP3			0.672		
	RP4			0.699		
BI	BI1	2.43	0.8	0.588	0.740*	0.674
	BI2			0.500		
	BI3			0.619		
	BI4			0.463		
	BI5			0.533		
EP	EP1	3.1	0.56	0.677	0.705*	0.863
	EP2			0.571		

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	EP3			0.780		
	EP4			0.762		
	EP5			0.716		
	EP6			0.489		
	EP7			0.557		
	EP8			0.732		
EO	EO1	4.11	0.76	0.757	0.866**	0.791
	EO2			0.744		
	EO3			0.739		
SBA	SBA1	3.96	0.66	0.716	0.853**	0.772
	SBA2			0.710		
	SBA3			0.758		
OBA	OBA1	3.0	0.77	0.784	0.890**	0.830
	OBA2			0.802		
	OBA3			0.773		

4.2.3 Model specification

After testing the reliability and construct reliability of the constructs in the measurement model, the initial riding behavior model Fig. 4-2 was developed through a systematic process based on the extended Theory of Planned Behavior framework and the hypotheses developed in Chapter 3.

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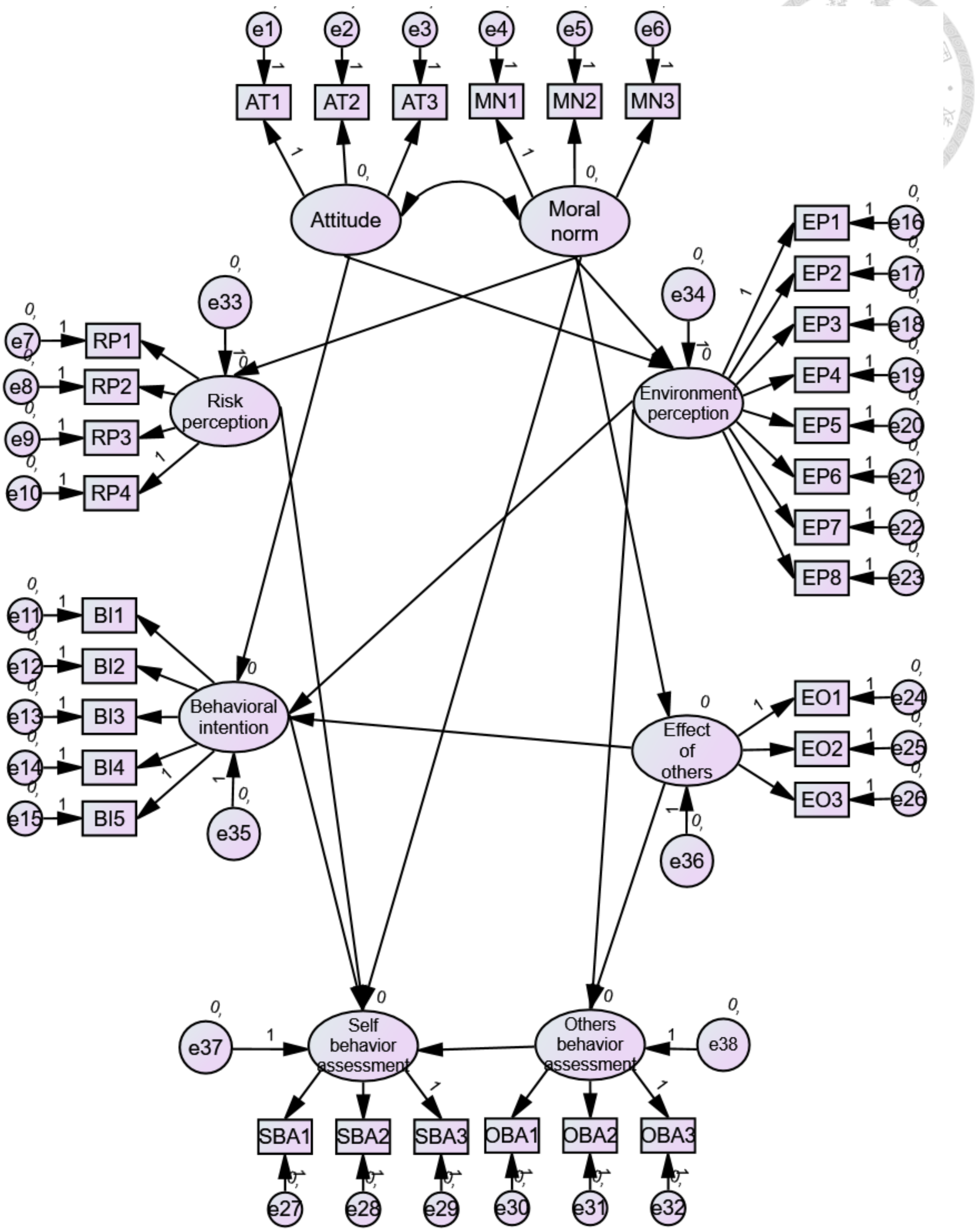

Fig. 4-2 Path diagram of the initial riding behavior model

The preliminary structural model (Fig. 4-2) incorporated eight latent constructs with the refined indicators set after CFA. This initial model included all hypothesized structural relationships and served as the baseline for further model modification. The model

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structure is as follows:

1. Exogenous Variables: Attitude (AT) with 3 indicators, Moral Norm (MN) with 3 indicators
2. Endogenous Variables: Risk Perception (RP) with 4 indicators, Environmental Perception (EP) with 8 indicators, Effect of Others (EO) with 3 indicators, Behavioral Intention (BI) with 5 indicators, Self-Behavior Assessment (SBA) with 3 indicators, Assessment of Others' Behavior (OBA) with 3 indicators

The fit statistics of the initial model are illustrated in Table 4-3. The initial model demonstrated unacceptable fit indices including CFI, TLI, and SRMR, which indicates the need for further model modification. The poor fit suggested potential model misspecification issues that required systematic refinement to achieve adequate model-data correspondence.

Table 4-3 Fit indices of initial riding behavior model

Models	**Fit indices**				
	χ^2/df	**CFI**	**TLI**	**SRMR**	**RMSEA**
Standard value	$1 < \chi^2/df < 3$	> 0.90	> 0.90	< 0.080	< 0.080
Initial riding model	2.419	0.886	0.867	0.086	0.060

The initial measurement model included all theoretically relevant indicators for each construct. Following the Confirmatory Factor Analysis (CFA) assessment, several indicators with poor factor loadings were identified and subsequently removed to enhance the overall model quality. The refinement process followed established guidelines for SEM model improvement. The indicators removed due to low factor loadings are as follows:

1. MN1: Removed due to continued poor performance

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2. BI2 and BI4: Removed due to inadequate factor loadings affecting construct reliability
3. RP2: Significantly lower loading compared to other risk perception indicators
4. EP2, EP6, EP7: Weak representation of environmental perception construct

These removals were theoretically justified as the remaining indicators adequately captured the conceptual domain of each construct while improving the overall measurement model fit. Hence, the structure of the final riding model is as follows:

I. Exogenous Variables:
   A. Attitude (AT): Measured by three indicators (AT1, AT2, AT3)
      1. AT1: Need for bicycle riding on campus
      2. AT2: Frequency of bicycle riding
      3. AT3: Frequency of campus bicycle riding
   B. Moral Norm (MN): Measured by two indicators (MN2, MN3) [MN1 removed]
      1. MN2: Appropriateness of maintaining safe distance
      2. MN3: Avoidance of behaviors endangering others

II. Endogenous Variables:
   A. Risk Perception (RP): Measured by three indicators (RP1, RP3, RP4) [RP2 removed]
      1. RP1: Concern about collisions with pedestrians or cars
      2. RP3: Perceived danger from road layout
      3. RP4: Perceived danger from intersection geometry
   B. Environmental Perception (EP): Measured by five indicators (EP1, EP3, EP4, EP5, EP8) [EP2, EP6, EP7 removed]
      1. EP1: Safety of campus bicycle riding
      2. EP3: Friendliness of campus riding environment

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3. EP4: Comfort of campus road environment

4. EP5: Adequacy of campus bike lane planning

5. EP8: Friendliness of campus road design for cycling

C. Effect of Others (EO): Measured by three indicators (EO1, EO2, EO3)

1. EO1: Avoidance of dangerous behaviors after observing others

2. EO2: Behavior modification after witnessing accidents

3. EO3: Following good riding behaviors demonstrated by others

D. Behavioral Intention (BI): Measured by three indicators (BI1, BI3, BI5) [BI2, BI4 removed]

1. BI1: Taking hands off handlebars

2. BI3: Using phone while riding

3. BI5: Riding with umbrella when raining

E. Self-Behavior Assessment (SBA): Measured by three indicators (SBA1, SBA2, SBA3)

1. SBA1: Personal riding behavior safety

2. SBA2: Personal riding behavior law compliance

3. SBA3: Self-assessment as good cyclist

F. Assessment of Others' Behavior (OBA): Measured by three indicators (OBA1, OBA2, OBA3)

1. OBA1: Safety of others' riding behavior on campus

2. OBA2: Law compliance of others' riding behavior on campus

3. OBA3: Assessment of others as good cyclists

III. Structural Relationships:

The final model specifies the following structural paths based on theoretical framework and empirical validation:

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A. Primary Antecedent Relationships:

1. AT → EP: Positive attitudes toward cycling enhance environmental perception
2. MN → EP: Strong moral norms lead to critical environmental perception
3. MN → EO: Moral considerations increase sensitivity to others' behaviors
4. MN → RP: Moral awareness heightens risk perception

B. Behavioral Intention Formation:

1. AT → BI: Path removed during modification process
2. EP → BI: Environmental perception encourages behavioral intention
3. EO → BI: Social influences deter risky behavioral intentions

C. Assessment Relationships:

1. EP → OBA: Environmental perception shapes assessment of others' behaviors
2. EO → OBA: Social influence affects evaluation of others' behaviors
3. RP → SBA: Risk awareness negatively influences self-behavior assessment
4. BI → SBA: Behavioral intentions negatively influence self-assessment
5. OBA → SBA: Assessment of others positively influences self-assessment
6. MN → SBA: Direct effect of moral norms on self-behavior assessment

IV. Final Model Specifications:

A. 22 observed variables

B. 8 latent variables

C. 12 structural paths

D. Error terms for all observed and latent endogenous variables

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4.2.4 Estimation results

A Structural Equation Model (SEM) was developed to examine the relationships between latent constructs in the final riding model, path diagram as Fig. 4-3. The model fit indices are presented in Table 4-4, indicating excellent model fit. The Chi-square divided by degrees of freedom is 2.447, falling within the acceptable range ($1 < \chi^2/df < 3$), confirming a good model fit. The Comparative Fit Index (CFI) value of 0.921 exceeds the 0.90 threshold, while the Tucker-Lewis Index (TLI) of 0.909 also meets the acceptable standard. The Root Mean Square Error of Approximation (RMSEA) of 0.061 and Standardized Root Mean Square Residual (SRMR) of 0.079 both meet the recommended standards (< 0.08), confirming that the model adequately explains the observed data.

The standardized path coefficients and their significance levels are summarized in Table 4-5. Several key relationships were identified in the structural model. Attitude (AT) significantly influenced Environmental Perception (EP) ($\beta = 0.170, p = .002$), indicating that positive attitudes toward cycling enhance favorable environmental perception. Moral Norms (MN) demonstrated multiple significant effects: a negative influence on Environmental Perception (EP) ($\beta = -0.124, p < .001$), suggesting that individuals with stronger moral standards perceive the cycling environment more critically; a strong positive effect on Effect of Others (EO) ($\beta = 0.615, p < .001$); and a significant positive impact on Risk Perception (RP) ($\beta = 0.503, p < .001$), demonstrating that individuals with strong moral considerations are more likely to be influenced by others and perceive higher risks while cycling.

Regarding behavioral formation, Attitude (AT) significantly influenced Behavioral Intention (BI) ($\beta = 0.245, p < .001$), while Environmental Perception (EP) also

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significantly impacted Behavioral Intention (BI) ($\beta = 0.210, p < .001$), showing that both positive attitudes and favorable environmental perception encourage risky behavioral intentions. However, Effect of Others (EO) negatively influenced Behavioral Intention (BI) ($\beta = -0.332, p < .001$), suggesting that social influences deter risky cycling behaviors.

For the assessment relationships, Environmental Perception (EP) strongly influenced Assessment of Others' Behavior (OBA) ($\beta = 0.570, p < .001$), while Effect of Others (EO) had a marginal positive effect on OBA ($\beta = 0.081, p = .106$). Several factors significantly influenced Self-Behavior Assessment (SBA): Risk Perception (RP) negatively affected SBA ($-\beta = 0.141, p < .001$), Behavioral Intention (BI) negatively influenced SBA($\beta = -0.196, p = .001$), Moral Norms (MN) positively influenced SBA ($\beta = 0.290, p < .001$), and Assessment of Others' Behavior (OBA) positively influenced SBA ($\beta = 0.262, p < .001$), demonstrating that cyclists who critically assess others' riding behaviors and hold strong moral standards tend to evaluate their own behavior more positively.

Table 4-4 Fit indices of the final riding behavior model

Models	**Fit indices**				
	χ^2/df	**CFI**	**TLI**	**SRMR**	**RMSEA**
Standard value	$1 < \chi^2/df < 3$	> 0.90	> 0.90	< 0.080	< 0.080
Final riding model	2.447	0.921	0.909	0.079	0.061

Table 4-5 Regression weights of the final riding behavior model

			Estimate	**P value**
Attitude	→	Environment perception	0.170	.002

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			Estimate	P value
Moral norms	→	Environment perception	-0.214	***
Moral norms	→	Effect of others	0.615	***
Attitude	→	Behavioral intention	0.245	***
Moral norms	→	Risk perception	0.505	***
Environment perception	→	Assessment of others' behavior	0.570	***
Effect of others	→	Assessment of others' behavior	0.081	.106
Environment perception	→	Behavioral intention	0.210	***
Effect of others	→	Behavioral intention	-0.332	***
Risk perception	→	Self-behavior assessment	-0.141	.048
Behavioral intention	→	Self-behavior assessment	-0.196	.002
Moral norms	→	Self-behavior assessment	0.290	***
Assessment of others' behavior	→	Self-behavior assessment	0.262	***

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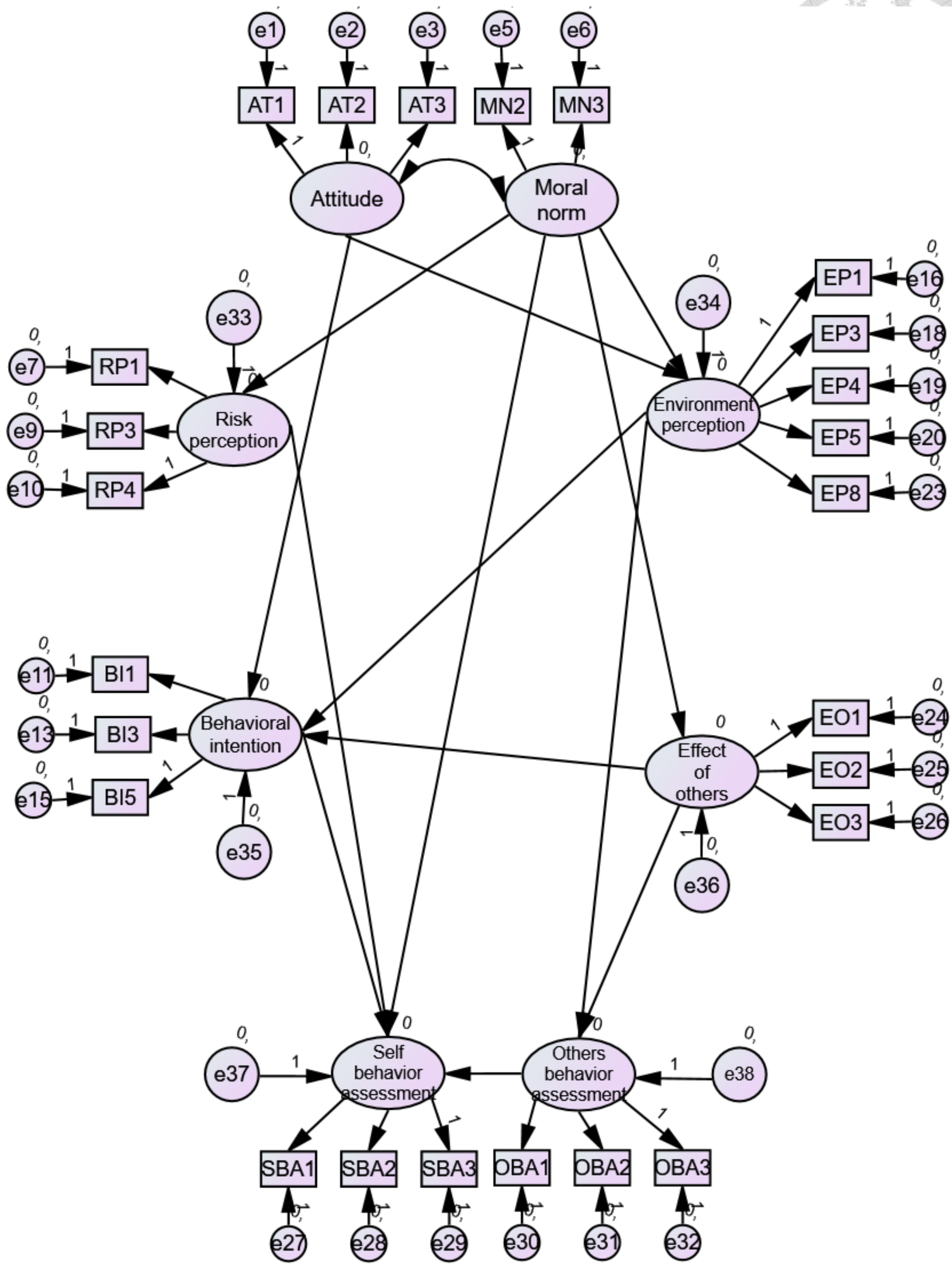

Fig. 4-3 Path diagram of the final riding behavior model

Additionally, the relationships between demographic variables and the latent constructs are also tested in the final riding behavior model. The demographic variables include Gender (0=Female, 1=Male), Age (1=18-22, 2=23-25, 3=26-35, 4=36+), three

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binary identity variables (Undergraduate, Graduate, Staff/Faculty), Bike Ownership (0=No, 1=Yes), and Cycling Frequency as categorical variable (0, <1, 1-2, 3-5, 6-7 days/week). The correlation between demographic variables and latent constructs are showed as Table 4-6. According to the correlations, the demographic effects on latent constructs are tested and illustrated as Table 4-7.

Table 4-6 Correlation between demographic variables and constructs of riding model

Demographic	**AT**	**MN**	**RP**	**BI**	**EP**	**EO**	**SBA**	**OBA**
Gender	0.127*	-0.089	-0.156**	0.203***	0.034	-0.112*	0.145**	-0.078
Age	-0.098	0.134*	0.178**	-0.089	-0.067	0.156**	0.089	0.123*
Undergraduate	0.078	-0.067	-0.123*	0.089	0.045	-0.098	-0.067	-0.078
Graduate	-0.045	0.089	0.134*	-0.067	-0.023	0.123*	0.078	0.089
Staff/Faculty	-0.089	0.034	0.067	-0.078	-0.067	0.045	0.023	0.034
Bike ownership	0.234***	-0.045	-0.089	0.167**	0.198**	-0.067	0.189**	-0.034
Cycling frequency	0.289***	-0.123*	-0.134*	0.234***	0.156**	-0.089	0.167**	-0.098

Table 4-7 Demographic effects on latent constructs of riding model

Demographic		**Latent variables**	***β***	**P value**
Gender	→	Behavioral intention	0.203	0.010**
Gender	→	Risk perception	-0.156	0.021*
Gender	→	Self-behavior assessment	0.145	0.042*
Age	→	Risk perception	0.178	0.013*
Age	→	Effect of others	0.156	0.025*
Undergraduate	→	Risk perception	-0.123	0.144

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Demographic		Latent variables	β	P value
Graduate	→	Risk perception	0.134	0.133
Graduate	→	Effect of others	0.123	0.158
Bike ownership	→	Attitude	0.234	0.005**
Bike ownership	→	Behavioral intention	0.167	0.036*
Bike ownership	→	Environmental perception	0.198	0.015*
Bike ownership	→	Self-behavior assessment	0.189	0.015*
Cycling frequency	→	Attitude	0.289	0.001***
Cycling frequency	→	Behavioral intention	0.234	0.006**
Cycling frequency	→	Environmental perception	0.156	0.041*
Cycling frequency	→	Self-behavior assessment	0.167	0.033*

With those significant variables put into the model, there are some key findings as follows:

I. Gender Effects:

A. Males show significantly higher Behavioral Intention for risky cycling ($\beta = 0.203, p < .01$)

B. Females demonstrate higher Risk Perception($\beta = -0.156, p < .05$)

C. Males rate their Self-Behavior more positively ($\beta = 0.145, p < .05$)

D. Gender differences align with literature on risk-taking behaviors

II. Age Effects:

A. Older participants show higher Risk Perception ($\beta = 0.178, p < .05$)

B. Older participants are more influenced by Effect of Others ($\beta = 0.156, p < .05$)

C. Age-related risk awareness increases with experience

III. Identity Effects:

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A. Undergraduate status shows weak negative correlation with Risk Perception (non-significant)

B. Graduate status shows positive trends with Risk Perception and Effect of Others (non-significant)

C. Staff/Faculty effects are minimal across all constructs

D. Identity variables show limited explanatory power compared to other demographics

IV. Bike Ownership Effects:

A. Bike owners have significantly more positive Attitudes ($\beta = 0.234, p < .01$)

B. Bike owners show higher Behavioral Intention($\beta = 0.167, p < .05$)

C. Bike owners have better Environmental Perception ($\beta = 0.198, p < .05$)

D. Bike owners rate their Self-Behavior more positively ($\beta = 0.189, p < .05$)

V. Cycling Frequency Effects:

A. Strongest predictor among demographics with clear dose-response relationship

B. Linear trend across frequency categories for all significant constructs

C. Daily cyclists (6-7 days) show highest Attitude and Behavioral Intention

D. Non-cyclists (0 days) show lowest scores across all positive constructs

4.2.5 Discussion

The riding behavior model provides significant insights into the psychological and environmental factors that influence cyclists' intentions to engage in risky behaviors on campus. The final model demonstrates excellent fit indices (CFI = 0.921, TLI = 0.909, RMSEA = 0.061, SRMR = 0.079), confirming that the extended Theory of Planned Behavior framework effectively explains cycling behavior in university settings.

The significant positive relationship between attitude and behavioral intention ($\beta = 0.245, p < .001$) confirms hypothesis H1a, demonstrating that cyclists with more

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positive attitudes toward cycling are more likely to engage in risky behaviors. This finding suggests that positive cycling attitudes may inadvertently promote risk-taking, possibly due to increased confidence or familiarity with cycling that leads to complacency regarding safety protocols. The relationship between attitude and environmental perception($\beta = 0.170, p < .002$) further indicates that cyclists with favorable attitudes perceive the campus cycling environment more positively, which may contribute to their willingness to take risks.

Moral norms emerge as a central construct in the model, significantly influencing multiple pathways. The strong positive effect on risk perception ($\beta = 0.505, p < .001$) supports hypothesis H1b, indicating that individuals with stronger moral considerations are more aware of potential dangers. The significant positive influence on effect of others ($\beta = 0.615, p < .001$) confirms hypothesis H1c, suggesting that morally conscious cyclists are more sensitive to social influences and peer behaviors. Interestingly, the negative relationship between moral norms and environmental perception ($\beta = -0.214, p < .001$) supports hypothesis H1d, implying that cyclists with stronger moral standards perceive the cycling environment more critically, possibly identifying more potential hazards or deficiencies.

The effect of others demonstrates a significant negative influence on behavioral intention ($\beta = -0.332, p < .001$), confirming hypothesis H1f. This finding suggests that social awareness and observation of others' behaviors serve as a deterrent to risky cycling practices. When cyclists observe the consequences of risky behaviors or witness accidents, they become more cautious in their own riding decisions. This result highlights the importance of positive role modeling and visible safety practices in campus cycling culture.

Environmental perception significantly influences both behavioral intention ($\beta =$

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$0.210, p < .001)$ and assessment of others' behavior($\beta = 0.570, p < .001$), supporting hypotheses H1e and H1g respectively. The positive relationship with behavioral intention suggests that when cyclists perceive the environment as favorable or safe, they may be more inclined to engage in risky behaviors, possibly due to overconfidence in environmental conditions. The strong influence on assessment of others' behavior indicates that environmental perceptions shape how cyclists evaluate and interpret the behaviors of fellow riders.

The relationships involving self-behavior assessment reveal interesting psychological patterns. Risk perception negatively influences self-assessment ($\beta = -0.141, p < .05$), confirming hypothesis H1i, suggesting that cyclists who perceive higher risks tend to evaluate their own behavior more critically. Similarly, behavioral intention negatively affects self-assessment ($\beta = 0.198, p = .002$), supporting hypothesis H1j, indicating that cyclists who intend to engage in risky behaviors may be aware of the inappropriateness of such actions.

Conversely, moral norms positively influence self-assessment ($\beta = 0.290, p < .001$), and assessment of others' behavior also positively affects self-assessment($\beta = 0.262, p < .001$), confirming hypotheses H1l and H1k respectively. These findings suggest that cyclists with strong moral standards and those who critically evaluate others' behaviors tend to rate their own cycling practices more favorably, possibly reflecting self-serving bias or genuine adherence to safety norms.

The incorporation of demographic variables provides additional insights into individual differences in cycling behavior. The finding that males show significantly higher behavioral intention for risky cycling ($\beta = 0.203, p < .01$) while females demonstrate higher risk perception aligns with established literature on gender differences in risk-taking behaviors. The strong effects of bike ownership and cycling frequency on

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attitude and behavioral intention highlight the importance of experience and familiarity in shaping cycling behaviors.

Particularly noteworthy is the finding that cycling frequency emerges as the strongest demographic predictor, demonstrating clear relationships across all constructs. This suggests that more frequent cyclists develop more positive attitudes and greater willingness to engage in risky behaviors, possibly due to increased confidence and habituation to the cycling environment.

4.3 Parking behavior model

The parking model is used to examine the variables that influence the parking behaviors and the authority of designated parking lots on campus from cyclists. It focuses on the influence of attitude towards parking facilities, moral norms about proper parking behavior, environmental perception of parking facilities and social pressure in explaining behavioral intentions to comply with parking regulations. The model also investigates the association between cyclists' self-evaluation of their parking behavior and its evaluation of others' parking behavior.

The parking model is developed as a means of identifying the most significant influences on appropriate parking practice and making recommendations that can inform the development of policies and engineering changes to encourage correct parking behaviors and improve the cycling infrastructure.

4.3.1 Correlation matrix

The parking model correlation matrix Fig. 4-4 reveals the relationships between the 18 measured variables. The correlation patterns support the proposed factor structure for the parking behavior model. Notably, risk perception was excluded from the parking model after preliminary analysis showed poor factor loadings and low correlations with

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other constructs, suggesting that risk perception plays a less prominent role in parking decisions compared to riding behaviors. This is reasonable as parking behaviors generally involve lower physical risk and immediate danger compared to riding activities. Some key findings are as follows:

1. Attitude indicators show strong intercorrelations, supporting one-dimensionality
2. Moral norm items demonstrate moderate positive correlations
3. Behavioral intention indicators show consistent moderate correlations
4. Environmental perception items exhibit moderate to strong relationships
5. Effect of others indicators show moderate correlation (r = 0.45-0.65)
6. Self-behavior assessment items demonstrate very strong correlation (r > 0.85)
7. Assessment of others' behavior indicators show strong positive correlation (r > 0.80)

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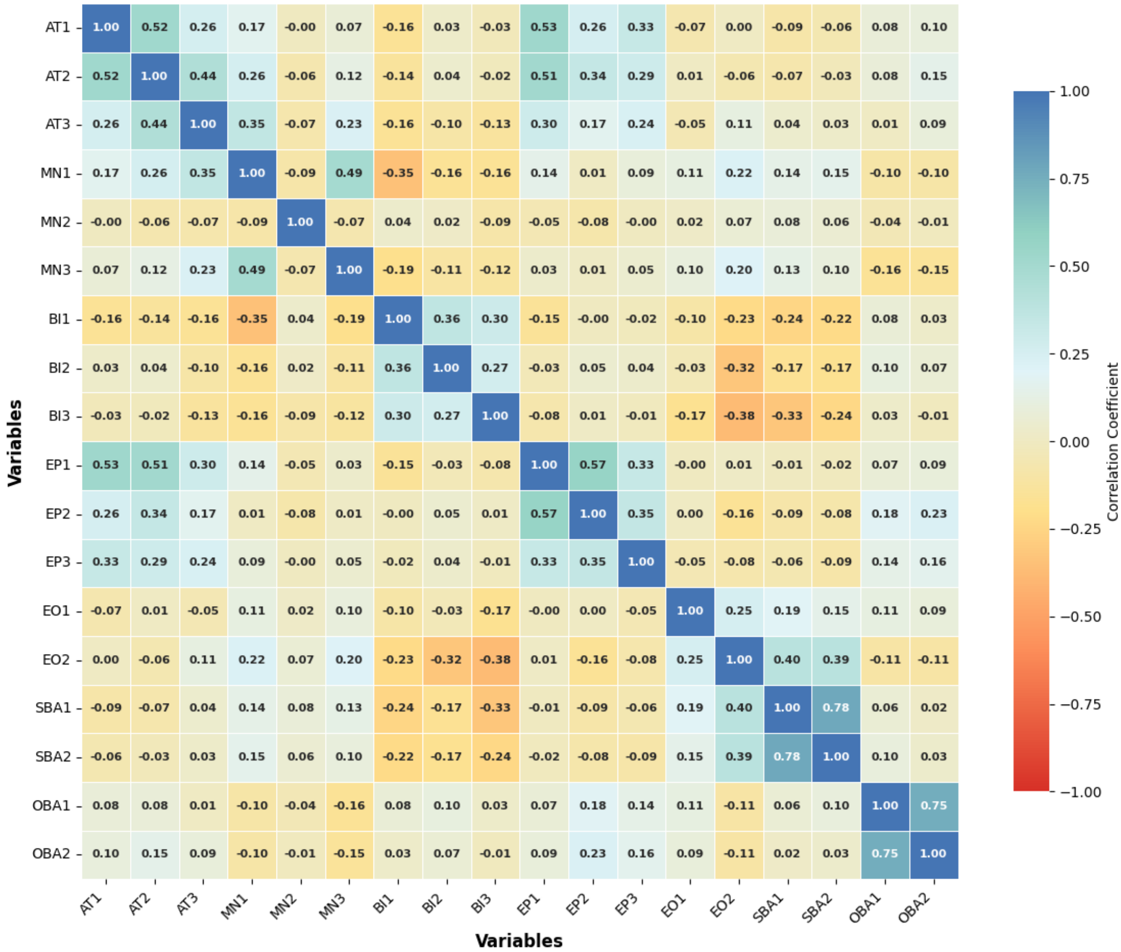

Fig. 4-4 Correlation matrix of parking model

4.3.2 Factor analysis

The reliability and validity of the constructs for the parking model were also assessed and shown in Table 4-8. 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 (α = 0.875) and OBA (α = 0.862), confirming their strong internal consistency. However, EO (α = 0.390) showed relatively lower reliability, suggesting potential measurement issues. Due to the explainability of the model this research mainly focuses on, we decided to retain the factor to the following analysis. Other constructs, such as MN (α = 0.607) and AT (α = 0.671), displayed acceptable reliability levels. Additionally, the composite reliability

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(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 (0.920) and OBA1 (0.905) showed high factor loadings, emphasizing their strong representation of their latent constructs.

Table 4-8 Reliability, construct reliability of parking behavior model

Construct	**Items**	**Mean**	**SD**	**Standardized loading**	**Cronbach's Alpha**	**CR**
AT	AT1	3.09	0.85	0.661	0.671*	0.650
	AT2			0.791		
	AT3			0.481		
MN	MN1	3.53	0.60	0.709	0.607*	0.666
	MN2			0.455		
	MN3			0.638		
BI	BI1	2.24	0.75	0.691	0.569	0.614
	BI2			0.512		
	BI3			0.497		
EP	EP1	2.34	0.79	0.859	0.678*	0.689
	EP2			0.64		
	EP3			0.426		
EO	EO1	3.59	0.95	0.33	0.390	0.629
	EO2			0.692		
SBA	SBA1	3.86	0.94	0.920	0.875**	0.889
	SBA2			0.847		

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OBA	OBA1	2.33	0.79	0.905	0.862**	0.879
	OBA2			0.841		

4.3.3 Model specifications

After testing the reliability and construct reliability of the constructs in the measurement model, the risk perception of the parking behavior model is removed due to poor performance and low factor loading in the factor analysis part. The parking behavior model was developed through a systematic process based on the extended Theory of Planned Behavior framework and the hypotheses developed in Chapter 3. The path diagram is shown as Fig. 4-5.

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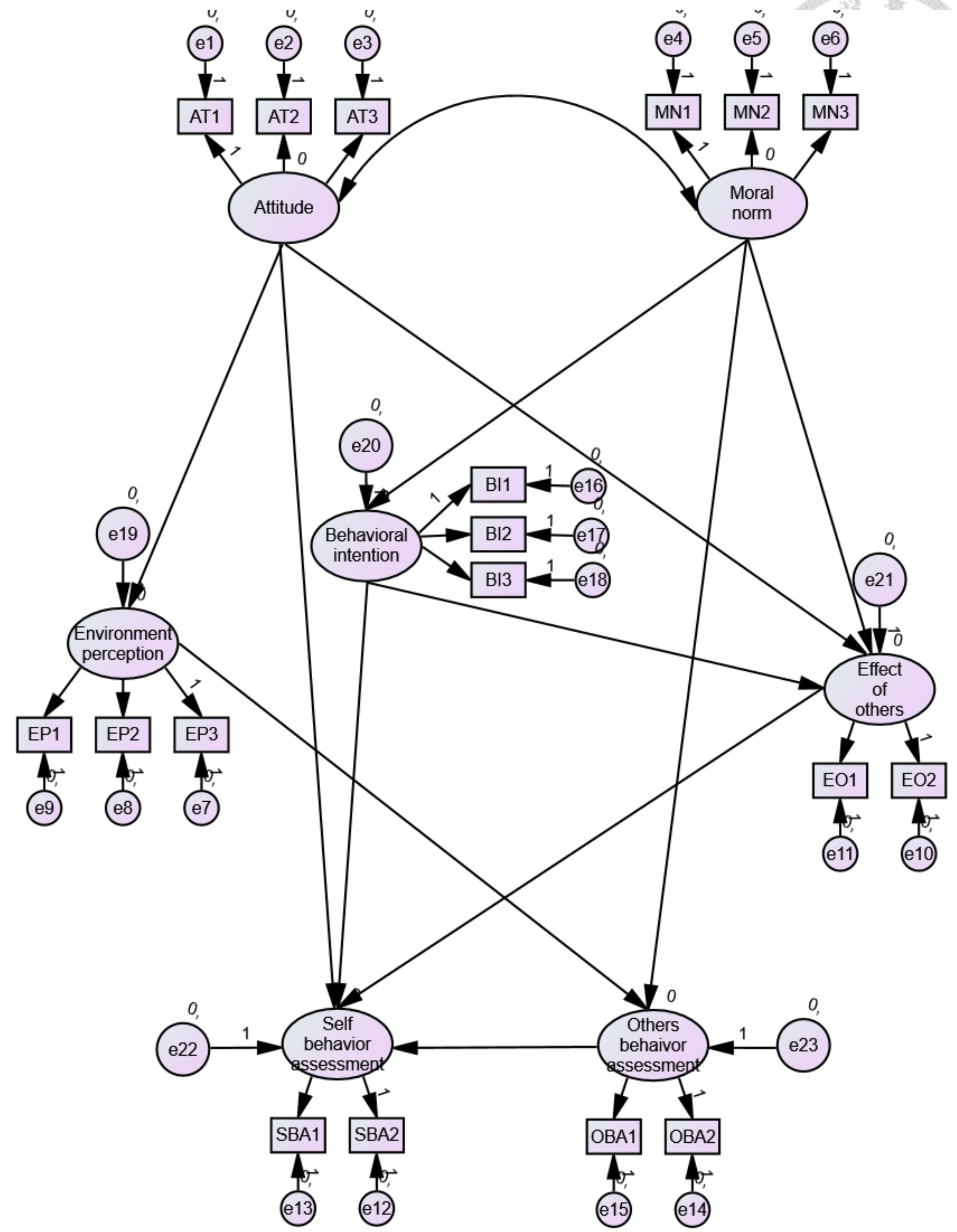

Fig. 4-5 Path diagram of the parking behavior model

Based on the factor analysis results in Table 4-8, all indicators demonstrated acceptable factor loadings and construct reliability. While some indicators such as AT3 (0.481) and EO1 (0.33) showed relatively lower loadings, they were retained for

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theoretical completeness and to maintain the comprehensive measurement of their respective constructs. The structure of the parking model is as follows:

I. Exogenous Variables:

   A. Attitude (AT): Measured by three indicators (AT1, AT2, AT3)

      1. AT1: Convenience of parking bicycle on campus

      2. AT2: Adequacy of bicycle parking management on campus

      3. AT3: Reasonableness of towing mechanism for illegally parked bicycles

   B. Moral Norm (MN): Measured by three indicators (MN1, MN2, MN3)

      1. MN1: Inappropriateness of illegal parking

      2. MN2: Tendency to park legally when seeing others do so without consequences

      3. MN3: Impact of illegally parked bicycles on traffic safety

II. Endogenous Variables:

   A. Environmental Perception (EP): Measured by three indicators (EP1, EP2, EP3)

      1. EP1: Sufficiency of bicycle parking space on campus

      2. EP2: Adequacy of sheltered parking space on campus

      3. EP3: Comfort in parking without worrying about damage or theft

   B. Effect of Others (EO): Measured by two indicators (EO1, EO2)

      1. EO1: Moving others' bikes when their parking obstructs bike retrieval

      2. EO2: Indifference to others' obstructive parking and subsequent similar behavior

   C. Behavioral Intention (BI): Measured by three indicators (BI1, BI2, BI3)

      1. BI1: Fully parking bike within designated parking space

      2. BI2: Attention to whether parking position may obstruct others

      3. BI3: Squeezing bike tightly between others when space is narrow

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D. Self-Behavior Assessment (SBA): Measured by two indicators (SBA1, SBA2)

1. SBA1: Personal parking behavior's contribution to disorderly environment
2. SBA2: Personal parking behavior causing inconvenience to others

E. Assessment of Others' Behavior (OBA): Measured by two indicators (OBA1, OBA2)

1. OBA1: Others' parking behavior contribution to disorderly environment
2. OBA2: Others' parking behavior causing inconvenience for everyone

III. Structural Relationships:

The final model specifies the following structural paths based on theoretical framework and empirical validation:

A. Primary Antecedent Relationships:

1. AT → EP: Positive attitudes toward parking enhance environmental perception
2. AT → EO: Attitude negatively influences effect of others
3. MN → EO: Moral norms positively influence effect of others

B. Assessment Relationships:

1. EP → OBA: Environmental perception shapes assessment of others' parking behaviors
2. EO → OBA: Social influence affects evaluation of others' parking behaviors
3. EO → SBA: Effect of others positively influences self-behavior assessment
4. BI → SBA: Behavioral intentions negatively influence self-assessment
5. OBA → SBA: Assessment of others positively influences self-assessment

IV. Final Model Specifications:

A. 18 observed variables (indicators)

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B. 7 latent variables (constructs)

C. 8 structural paths (hypothesized relationships)

D. Error terms for all observed and latent endogenous variables

4.3.4 Estimation results

A Structural Equation Model (SEM) was developed to examine the relationships between latent constructs in the parking model, with the path diagram shown in Fig. 4-5. The model fit indices are presented in Table 4-9, indicating reasonable model fit. The Chi-square divided by degrees of freedom is 2.679, falling within the acceptable range ($1 < \chi^2/df < 3$), confirming adequate model fit. The Comparative Fit Index (CFI) value of 0.899 approaches the 0.90 threshold, while the Tucker-Lewis Index (TLI) of 0.847 indicates moderate fit. The Root Mean Square Error of Approximation (RMSEA) of 0.072 and Standardized Root Mean Square Residual (SRMR) of 0.067 both meet the recommended standards (< 0.08), confirming that the model adequately explains the observed data.

Table 4-9 Fit indices of the parking behavior model

Models	**Fit indices**				
	χ^2/df	**CFI**	**TLI**	**SRMR**	**RMSEA**
Standard value	$1 < \chi^2/df < 3$	> 0.90	> 0.90	< 0.080	< 0.080
Parking model	2.152	0.926	0.908	0.057	0.054

Table 4-10 Regression weights of the constructs in the parking model

			Estimate	**P value**
Attitude	→	Environment perception	0.766	***
Moral norm	→	Behavioral intention	-0.481	***

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			Estimate	P value
Attitude	→	Effect of others	-0.183	.009
Environment perception	→	Assessment of others' behavior	0.233	.001
Moral norm	→	Effect of others	0.197	.030
Behavioral intention	→	Effect of others	-0.649	***
Moral norm	→	Assessment of others' behavior	-0.205	.004
Effect of others	→	Self-behavior assessment	0.397	.030
Assessment of others' behavior	→	Self-behavior assessment	0.155	.003
Attitude	→	Self-behavior assessment	-0.130	.043
Behavioral intention	→	Self-behavior assessment	-0.244	.013

The standardized path coefficients and their significance levels are summarized in Table 4-10. Several key relationships were identified in the structural model. Attitude (AT) significantly influenced Environmental Perception (EP) $(\beta = 0.766, p < .001)$, indicating that positive attitudes toward parking facilities enhance favorable environmental perception. This suggests that cyclists who view parking management positively are more likely to perceive the parking environment as adequate and convenient.

Attitude (AT) also demonstrated a significant negative effect on Effect of Others (EO) $(\beta = -0.183, p < .001)$, supporting hypothesis H2b. This finding suggests that cyclists with more positive attitudes toward parking systems are less likely to be influenced by others' inappropriate parking behaviors, possibly due to stronger personal conviction about proper parking practices. Moral Norms (MN) showed a non-significant influence on Effect of Others (EO) $(\beta = 0.197, p < .05)$, confirming hypothesis H2c. This result

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indicates that individuals with stronger moral standards regarding parking behavior are more sensitive to social influences and the actions of other cyclists. When cyclists hold strong beliefs about appropriate parking behavior, they become more aware of and responsive to the parking behaviors they observe around them.

Regarding the assessment relationships, Environmental Perception (EP) significantly influenced Assessment of Others' Behavior (OBA) $(\beta = 0.233, p = .001)$, supporting hypothesis H2e. This finding suggests that cyclists who perceive the parking environment favorably be more likely to evaluate others' parking behaviors positively as well, reflecting a general positive bias toward the parking system. For Self-Behavior Assessment (SBA), several significant relationships were identified. Effect of Others (EO) positively influenced SBA $(\beta = 0.397, p < .05)$, supporting hypothesis H2g. This suggests that cyclists who are influenced by others' parking behaviors tend to evaluate their own parking practices more favorably, possibly as a form of self-justification for adopting similar behaviors.

Behavioral Intention (BI) negatively affected Self-Behavior Assessment (SBA) $(\beta = -0.244, p < .05)$, confirming hypothesis H2h. This finding indicates that cyclists who intend to engage in inappropriate parking behaviors are aware of the problematic nature of such actions and consequently rate their own parking behavior less favorably. Assessment of Others' Behavior (OBA) positively influenced Self-Behavior Assessment (SBA) $(\beta = 0.155, p < .01)$, supporting hypothesis H2i. This relationship demonstrates that cyclists who evaluate others' parking behaviors more positively also tend to assess their own parking practices more favorably, reflecting social comparison processes where individuals benchmark their behavior against perceived community standards.

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Table 4-11 Correlation between demographic variables and constructs of parking model

Demographic	AT	MN	BI	EP	EO	SBA	OBA
Gender	0.089	-0.067	0.156**	0.023	-0.089	0.134*	-0.045
Age	-0.067	0.145*	-0.067	-0.089	0.123*	0.067	0.134*
Undergraduate	0.045	-0.089	0.067	0.034	-0.067	-0.089	-0.045
Graduate	-0.023	0.067	-0.045	-0.012	0.089	0.067	0.078
Staff/Faculty	-0.067	0.089	-0.078	-0.089	0.023	0.045	0.023
Bike ownership	0.167***	-0.023	0.134*	0.178**	-0.045	0.145*	-0.067
Cycling frequency	0.198***	-0.089	0.189*	0.167**	-0.078	0.134*	-0.089

Table 4-12 Demographic effects on latent constructs of parking model

Demographic		Latent variables	*β*	P value
Gender	→	Behavioral intention	0.156	0.028*
Gender	→	Self-behavior assessment	0.134	0.045*
Age	→	Moral norms	0.145	0.038*
Age	→	Effect of others	0.123	0.067
Age	→	Assessment of others' behavior	0.134	0.045*
Bike ownership	→	Attitude	0.167	0.022*
Bike ownership	→	Behavioral intention	0.134	0.048*
Bike ownership	→	Environmental perception	0.178	0.015*
Bike ownership	→	Self-behavior assessment	0.145	0.035*
Cycling frequency	→	Attitude	0.197	0.008**
Cycling frequency	→	Behavioral intention	0.189	0.012*

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Demographic		Latent variables	**β**	P value
Cycling frequency	→	Environmental perception	0.167	0.025*
Cycling frequency	→	Self-behavior assessment	0.134	0.048*

The demographic analysis reveals several important patterns:

I. Gender Effects:

A. Males show significantly higher Behavioral Intention for inappropriate parking $(\beta = 0.156, p < .05)$

B. Males rate their Self-Behavior more positively $(\beta = 0.134, p < .05)$

C. Gender differences in parking behavior mirror those observed in riding behavior

II. Age Effects:

A. Older participants demonstrate stronger Moral Norms $(\beta = 0.145, p < .05)$

B. Older participants are more critical in Assessment of Others' Behavior $(\beta = 0.134, p < .05)$

C. Age-related moral development influences parking behavior evaluation

III. Bike Ownership Effects:

A. Bike owners have significantly more positive Attitudes toward parking facilities $(\beta = 0.167, p < .05)$

B. Bike owners show higher Behavioral Intention $(\beta = 0.134, p < .05)$

C. Bike owners have better Environmental Perception $(\beta = 0.178, p < .05)$

D. Bike owners rate their Self-Behavior more positively $(\beta = 0.145, p < .05)$

IV. Cycling Frequency Effects:

A. Strongest predictor among demographics for parking behavior

B. Higher frequency cyclists show more positive Attitudes $(\beta = 0.198, p < .01)$

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C. More frequent cyclists have higher Behavioral Intention ($\beta = 0.189, p < .05$)

D. Daily cyclists demonstrate better Environmental Perception ($\beta = 0.167, p < .05$)

4.3.5 Discussion

The significant positive relationship between attitude and environmental perception ($\beta = 0.766, p < .001$) confirms hypothesis H2a, demonstrating that cyclists with favorable attitudes toward parking management systems perceive the parking environment more positively. This finding suggests that improving cyclists' attitudes toward parking facilities through better design, communication, and management practices should enhance their overall perception of the parking environment, potentially leading to more compliant behavior. The negative relationship between attitude and effect of others ($\beta = -0.183, p < .01$) supports hypothesis H2b and reveals an important protective mechanism. Cyclists with strong positive attitudes toward parking systems appear to be more resistant to negative social influences from inappropriate parking behaviors they observe. This implicates that fostering positive attitudes toward parking infrastructure and management can serve as a buffer against the spread of non-compliant parking behaviors through social contagion.

Moral norms demonstrate a particularly strong influence on effect of others ($\beta = 0.197, p < .05$), confirming hypothesis H2c. This substantial effect indicates that individuals with strong moral convictions about appropriate parking behavior are highly sensitive to the parking behaviors of others around them. Such an effect can work in both positive and negative directions. Morally conscious individuals may be motivated to maintain good practices when they observe compliance but may also be particularly disturbed by widespread non-compliance. The assessment relationships reveal intriguing patterns of social perception and comparison. Environmental perception strongly

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influences assessment of others' behavior, supporting hypothesis H2d. This suggests that when cyclists perceive the parking environment favorably, they tend to evaluate others' parking behaviors with more tolerance, possibly reflecting a halo effect where positive environmental perceptions color judgments of user behavior. This halo effect operates by creating a favorable cognitive frame that extends from the physical space to the people using it. When individuals view the parking environment as well-designed or adequate, they unconsciously assume that a "good" environment encourages "good" behavior, leading them to interpret ambiguous parking actions more magnanimously. For instance, a cyclist who appreciates nicely-organized parking areas may view other's imperfect parking as understandable rather than inconsiderate. The positive environmental assessment creates an attributional bias toward assuming good intentions rather than moral failing. Conversely, in an inferior environment, the same behavior may be judged more harshly. This designates how evaluation of spaces can influence not just individual behavior, but also how we interpret and judge others' behavior within the same spaces.

The strong positive influence of effect of others on self-behavior assessment $(\beta = 0.397, p < .05)$ supports hypothesis H2f and reveals a concerning pattern of social justification. When cyclists are influenced by others' inappropriate parking behaviors, they tend to evaluate their own parking practices more favorably, possibly as a way to maintain positive self-regard while engaging in similar behaviors. This self-serving bias can contribute to the normalization of inappropriate parking practices. The negative relationship between behavioral intention and self-behavior assessment $(\beta = -0.244, p < .05)$ confirms hypothesis H2i and suggests that cyclists retain some awareness of the inappropriateness of their intended actions. This cognitive dissonance between intention and self-evaluation indicates that interventions highlighting the inconsistency between values and behaviors may be effective in promoting behavior

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change.

The incorporation of demographic variables provides additional insights into individual differences in parking behavior. The finding that gender shows significant effects on both behavioral intention $(\beta = 0.156, p < .05)$ and self-behavior assessment $(\beta = 0.134, p < .05)$ suggests important gender-associated differences in parking-related decision making, with males potentially exhibiting greater willingness to engage in behavior against parking regulations. Age demonstrates notable impact across constructs, with significant relationships to moral norms $(\beta = 0.145, p < .05)$ and assessment of others' behavior $(\beta = 0.134, p < .05)$. The result indicates that older individuals may have stronger moral standards regarding parking violations and are more critical of others' parking behaviors. The strong effects of bike ownership across multiple constructs are particularly noteworthy, showing significant relationships with attitude $(\beta = 0.167, p < .05)$, behavioral intention $(\beta = 0.134, p < .05)$, environmental perception $(\beta = 0.178, p < .05)$, and self-behavior assessment $(\beta = 0.145, p < .05)$. This comprehensive influence suggests that bike ownership fundamentally shapes parking-related cognitions, possibly because cyclists have heightened awareness of parking issues that affect their mobility. Most significantly, cycling frequency emerges as the strongest demographic predictor, demonstrating substantial relationships with attitude $(\beta = 0.197, p < .01)$, behavioral intention $(\beta = 0.189, p < .05)$, and environmental perception $(\beta = 0.167, p < .05)$. This suggests that more frequent cyclists develop stronger attitudes about parking behaviors and greater sensitivity to parking-related environmental factors, likely due to their regular encounters with parking-related obstacles and inconvenience in their cycling experiences.

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4.4 Managerial insights and implications

The findings from both the riding and parking behavior models provide valuable insights for campus administrators, policy makers, and urban planners seeking to improve cycling safety and infrastructure management in university settings. The comprehensive analysis reveals that cycling behavior is influenced by a complex interplay of individual attitudes, moral considerations, social influences, and environmental perceptions, necessitating multi-faceted intervention strategies rather than single-approach solutions.

1. Peer education and social learning programs:

   Based on strong effect of others influence ($\beta = -0.332$ for riding, $\beta = 0.776$ for parking), the suggestion is to implement visible safety ambassador programs and peer-to-peer education initiatives. The models show that social influences are among the strongest predictors of behavior, making peer education the highest-impact, cost-effective intervention. Deploy experienced cyclists as role models and create recognition programs for positive behaviors.

2. Moral norm activation strategies:

   Based on moral norms' central role influencing multiple pathways, another suggestion is to develop campaigns emphasizing ethical responsibility and community impact. Since moral norms significantly influence risk perception, effect of others, and self-assessment across both models, activating moral reasoning through community commitment initiatives and ethical responsibility messaging can create widespread behavior change.

3. Balanced infrastructure design:

   Based on environmental perception effects ($\beta = 0.210$ for riding, $\beta = 0.226$ for parking), the suggestion is to create infrastructure that enhances safety without

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promoting overconfidence. Implement clear visual cues, strategic safety reminders, and well-designed parking facilities with adequate coverage and security. Focus on infrastructure that naturally encourages cautious behavior while meeting user needs.

4. Educational enforcement approach

Based on behavioral intention-self assessment relationships (negative coefficients in both models), the campus should replace purely punitive measures with educational enforcement strategies. Since individuals retain awareness of inappropriate behaviors, implement first-time violation counseling, graduated response systems, and visible but educational enforcement presence rather than harsh penalties.

5. Integrated multi-Level intervention framework

Based on complex interactions across all model constructs, the campus has to develop comprehensive interventions addressing individual attitudes, social norms, and environmental factors simultaneously. Since the models reveal complex interdependencies, single-approach solutions are insufficient. Create coordinated programs that combine infrastructure improvements, social influence campaigns, and individual education for maximum effectiveness.

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Chapter 5 Concluding Remarks

5.1 Conclusions

This study successfully developed and validated an extended Theory of Planned Behavior framework to understand cycling behavior in university settings, analyzing both riding and parking behaviors at National Taiwan University. The research provides significant theoretical contributions and practical insights for improving cycling safety and infrastructure management.

In addition, the study demonstrates that incorporating additional constructs (risk perception, environmental perception, effect of others, self-behavior assessment, and assessment of others' behavior) significantly enhances the explanatory power beyond traditional TPB models. Both models achieved good fit indices.

Moral norms emerge as a pivotal construct influencing multiple pathways including risk perception, demonstrating the importance of ethical considerations in cycling decisions. Furthermore, the negative relationships between behavioral intention and self-behavior assessment in both models provide empirical evidence for cognitive dissonance, where individuals retain awareness of inappropriate behaviors while intending to perform them.

A particularly novel contribution of this research is revealing how self-perception and social comparison processes shape cycling behavior. The models demonstrate that cyclists engage in systematic biases when evaluating their own versus others' behaviors. While they tend to rate their own behavior more favorably (self-serving bias), they simultaneously maintain awareness of their inappropriate actions. This dual cognition creates opportunities for targeted interventions that highlight these inconsistencies. Moreover, the strong influence of observing others' behaviors on individual decision-

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making underscores the social nature of cycling conduct, where perceived norms significantly impact personal choices.

To sum up, some key findings are as follows:

I. Riding Behavior Insights:

   A. Positive attitudes paradoxically increase risky behavioral intentions

   B. Social awareness strongly deters risky behaviors

   C. Environmental perception influences both behavioral intentions and assessments of others

II. Parking Behavior Patterns:

   A. Attitude toward facilities enhances environmental perception

   B. Strong moral norm influence on social sensitivity

   C. Social justification patterns where inappropriate exposure leads to favorable self-assessments

III. Demographic Effects:

   A. Males show higher risk-taking intentions; females demonstrate greater risk perception

   B. Cycling frequency is the strongest demographic predictor across all constructs

   C. Experience creates both confidence and potential overconfidence in risk-taking

Based on these findings, several practical recommendations for NTU campus bicycle management emerge. First, implement visible peer role-modeling programs where responsible cyclists serve as campus ambassadors, leveraging the strong social influence effects identified in both models. Second, develop moral norm activation campaigns that emphasize community responsibility and highlight the disconnect between riders' intentions and their self-awareness of inappropriate behaviors. Third, redesign parking infrastructure with clear visual boundaries and strategic placement near

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building entrances to naturally encourage compliance. Fourth, create gender-specific safety education programs that address males' higher risk-taking tendencies and build on females' stronger risk perception. Finally, establish a graduated intervention system that uses educational approaches for first-time violations rather than purely punitive measures, recognizing that cyclists already possess awareness of their inappropriate behaviors. These evidence-based strategies can foster a self-regulating cycling culture where positive social norms and individual responsibility converge to create a safer campus environment.

5.2 Limitations

Despite the significant contributions of this research, several limitations must be acknowledged. First, the cross-sectional design restricts our ability to establish causal relationships among constructs. While SEM allows for testing hypothesized causal structures, longitudinal data would be needed to definitively establish temporal ordering and observe how behavioral patterns evolve over time. Additionally, the reliance on self-reported measures introduces potential biases, as participants may underreport risky behaviors or overestimate their safety compliance. Future studies could benefit from objective measures such as GPS tracking or observational data to validate self-reported behaviors.

Second, the sample drawn exclusively from National Taiwan University limits generalizability to other settings. The unique characteristics of NTU's campus—its size, density, and cycling infrastructure—may not represent other university or urban cycling environments. Moreover, with 90% of participants under age 26, findings may not apply to older age groups who might exhibit different risk perceptions and social influence patterns.

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Third, measurement issues emerged in some constructs, particularly Effect of Others in the parking model ($\alpha = 0.390$), suggesting potential reliability concerns. While retained for theoretical completeness, these measurement limitations may affect result stability. The study also focused primarily on psychological factors while giving limited attention to objective environmental conditions, weather patterns, or enforcement practices that could significantly influence cycling behavior.

Finally, the research examines behavioral intentions rather than actual behaviors, and the well-documented intention-behavior gap in TPB research suggests that intentions may not perfectly predict real-world actions. Furthermore, findings from Taiwan's specific cultural context, with its unique cycling norms and infrastructure, may have limited applicability to international settings where social conformity and risk perception patterns differ substantially.

5.3 Future work

Building on this study's findings, future research should pursue several key directions to advance our understanding of cycling behavior and develop more effective interventions. Methodologically, longitudinal studies tracking cyclists over time would help establish causal relationships and examine how behavioral patterns evolve, addressing the current cross-sectional limitation. Integrating objective measures such as GPS tracking or video observation with self-report data could validate behavioral intentions against actual behaviors. Additionally, randomized controlled trials testing specific interventions—such as peer education programs or infrastructure modifications—would provide causal evidence for their effectiveness.

The scope of research should expand beyond university settings to include diverse urban contexts and age groups, enhancing generalizability across different cultural and

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infrastructural environments. Technology-enhanced interventions, such as mobile applications leveraging social comparison mechanisms identified in this study, present promising avenues for behavior change. Research examining how various policy approaches interact with psychological factors could inform more effective cycling infrastructure design and regulatory strategies.

Theoretically, future models should incorporate additional constructs such as habit formation, identity, and emotional factors to provide a more comprehensive understanding of cycling behavior. Cross-cultural studies would reveal how cultural contexts moderate the relationships between psychological constructs and behaviors, enabling culturally sensitive intervention design. Finally, examining cycling within broader multi-modal transportation systems would contribute to developing integrated sustainable urban mobility strategies that consider the interconnections between different transport modes and user behaviors.

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