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Towards safer bicyclist responses to the presence of a truck near an urban loading zone: Analysis of bicyclist perceived level of comfort

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ABSTRACT

Introduction: While sophisticated plans have been adopted nationally and globally to increase bicycling's share of daily commutes, safety concerns have negatively impacted targeted bicycling growth. To investigate people's preferences for bicycling in dense urban areas, it is important to recognize how bicycling perceived level of comfort (PLOC) is constructed and how it could relate to safe versus risky behavior while interacting with motorized modes of transportation. *Method:* To examine these issues, we analyzed results from an online survey with 342 participants. Structural Equation Modeling (SEM) was employed to systematically investigate the construct of bicycling PLOC and simultaneously analyze bicyclists' responses to the presence of a truck in the adjacent lane near an urban loading zone. *Results:* SEM estimation results indicated that participants who said that they engaged in more frequent distracted bicycling reported lower PLOC. On the other hand, those who felt that road users were more lawful and predictable, and who had more bicycling experience, reported higher levels of PLOC. Participants who bicycled for commuting purposes, who made shorter trips, who bicycled more frequently, and who had more exposure to downtown bicycling also reported higher levels of PLOC. Finally, findings showed that higher PLOC was significantly associated with the choice of a safe, rather than a risky response to the presence of a truck, suggesting that a way to improve bicyclist safety would be to build an environment that could increase bicyclists' PLOC.

1. Introduction

Growing concerns over the effects of motor-vehicle use on the environment, health, safety, and community livability have contributed to a paradigm shift from motorized to nonmotorized modes of travel (also known as active transportation) in transportation planning. Notably, as traffic congestion grows, many cities are encouraging bicycling as a functional alternative to driving passenger cars, especially in dense urban areas. Bicycling is less infrastructure-intensive than public transportation and has a much longer range than walking. As such, many U.S. cities have plans to increase their bicycle mode share. For example, Portland, Oregon, adopted a bicycle plan that aims to achieve a 25% bicycle mode share by 2030 (PBOT, 2010).

While sophisticated plans have been adopted nationally and globally to increase bicycling's share of daily commutes, safety concerns have negatively impacted targeted bicycling growth. In the United States, despite a decrease in the total number of motor-vehicle traffic fatalities, the proportion of bicyclist fatalities among total traffic fatalities increased from 1.47% in 2003 (629/42,884 bicyclist/total fatalities) to 2.33% in 2015 (818/32,166 bicyclist/total fatalities) (FARS, 2017). Additionally, with 45,000 recorded injuries, bicyclists constituted approximately 1.5% of total traffic injures in 2015 (NHTSA, 2017b). Given that in 2015, the bicycle commuting rate in the United States was only 0.6% (McLeod, 2016), bicyclists' overrepresentation in traffic fatalities and injuries represent a clear traffic safety concern. The perception of comfort and safety has influenced the decision to bicycle and the frequency of bicycling. Several studies have shown that people are discouraged from bicycling or are unwilling to ride a bicycle because of comfort and safety concerns, including traffic volume, motor-vehicle speed, lack of appropriate bicycle facilities, and driver behavior (Damant-Sirois & El-Geneidy, 2015; Dill & Voros, 2007; McNeil, Monsere, & Dill, 2015; Sanders, 2013).

Several studies have examined bicyclist behavior during different types of interactions with motorized traffic, especially at intersections. Bicyclist behavior has been extensively analyzed by looking into bicycle conflicts with left-turning vehicles (Stipancic,

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Zangenehpour, Miranda-Moreno, Saunier, & Granié, 2016), right-turning vehicles (Hurwitz & Abadi, 2018), and through moving vehicles (Plumert, Kearney, Cremer, Recker, & Strutt, 2011). Additionally, a few studies have inspected bicyclist interactions with vehicular modes other than passenger cars. Specifically, bicyclist behaviors during interactions with buses (De Ceunynck et al., 2017), motorcycles (Liu et al., 2012), autonomous vehicles (Vissers, Kint, Schagen, & Hagenzieker, 2017), and trucks (Pokorny, 2018) have been identified as determinants of bicycling safety in urban areas. Truck traffic has been found to play a pivotal role in bicyclists' perceptions of comfort and safety in urban environments (Winters, Davidson, Kao, & Teschke, 2011). One study in Manhattan, NY found that about 14% of freight vehicles conflicted with a bicycle in dense urban areas such that bicyclists were required to either deviate from the bicycle lane, or move further into the travel/parking lane or completely stop (Conway, Thuillier, Dornhelm, & Lownes, 2013). Bicycle conflicts with freight vehicles often result in severe consequences as demonstrated by the fact that large trucks are the only vehicle classification to be overrepresented in bicyclist fatalities in recent years. For example, large trucks were involved in 10.15% of bicyclist fatalities in United States in 2013, despite comprising only 3.94% of registered vehicles (NHTSA, 2015, 2017a). Bicycling alongside truck traffic decreased bicyclist perceived level of comfort by more than 40% (Abadi & Hurwitz, 2018). As such, the significant impact of truck presence on bicyclist safety and comfort could hinder the projected growth in bicycling, especially in dense urban areas.

As long as bicyclist perceptions of comfort and safety are not fully understood, they are likely to remain as significant barriers for bicycling growth. To investigate people's preferences for bicycling in dense urban areas, it is important to recognize how bicycling perceived level of comfort (PLOC) is constructed and how it could relate to safe versus risky behavior while interacting with motorized modes of transportation, specifically bicycle-truck conflicts. This study employed an online survey to investigate which bicyclist characteristics contribute to PLOC.

2. Background

2.1. Bicyclist characteristics

The present study hypothesizes a direct interaction between bicyclists' behavioral norms and behavioral outcomes. This interaction is well documented in previous research. Established theories in social sciences have shown that certain attitudes and perceptions are predictive of people's behavior. For example, social cognitive theory investigate the interaction of individuals and their immediate environment to analyze behavioral changes (Bandura, 2004) and the theory of planned behavior relates the performance of a behavior to a joint function of intentions and perceived behavioral control (Ajzen, 1991). Researchers in the field of transportation engineering have extensively used these theories to investigate the interaction between behavioral norms and behavioral outcomes. For example, exploring the use of individualized marketing as a transportation demand management strategy, Dill and Mohr (2010) identified that attitudes, social norms, and perceived behavioral control significantly impact travel behavior. Several studies have identified components of these interactions within the field of active transportation planning (see Dill, Mohr, & Ma, 2014 for a complete list). For instance, Lemieux and Godin (2009) found that variables such as past behavior, attitudes, and habits play an important role in explaining walking/bicycling to school, Beenackers, Kamphuis, Mackenbach, Burdorf, and van Lenthe (2013) found that perceived safety, social factors, and psychological cognitions such as attitudes, self-efficacy, and intentions are associated with leisure-time walking, Lee (2016) found that attitude, subjective norm, and perceived behavior control affect the intention for leisure-time walking among older adults. Piatkowski, Marshall, and Johnson (2017) found that bicyclists' behavioral norms such as texting/talking, wearing helmet, and obeying rules of the road influence their aggressive versus benevolent responses, and finally Li (2019) found that the probability to choose bike-sharing for commute trips among daily commuters is affected by their personal attitudes such as "willingness to be green" and "satisfaction with cycling environment." While bicyclist behavioral studies have evaluated a wide range of bicyclist characteristics, none have considered the influence of PLOC on bicyclist behavior.

2.2. Bicyclist PLOC

Bicyclists' perceptions of comfort and safety have been considered from a variety of different perspectives. At a macroscopic level, ample studies investigated transportation network connectivity and accessibility for bikeways to analyze bicycling level of stress (e.g., Buehler & Dill, 2016; Lowry, Callister, Gresham, & Moore, 2012; Mekuria, Furth, & Nixon, 2012). In these efforts, level of stress has been linked to actual safety outcomes (Vogt, 2015), bicycle facility type (Blanc & Figliozzi, 2016), speed data (Joo, Oh, Jeong, & Lee, 2015), and even prioritization of future bicycle infrastructure investment (Semler, Sanders, Buck, Graham, Pochowski, Dock, & Board, 2017). At this level, perception of comfort and safety is reported in various scales such as the bicycle compatibility index (Harkey, Reinfurt, & Knuiman, 1998), bicycle stress level (Sorton & Walsh, 1994), and bicycle level of service (TRB, 2010).

On the other hand, at a microscopic level, perception of comfort and safety has been evaluated among individual bicyclists (e.g., Ng, Debnath, & Heesch, 2017). Previous research showed that the PLOC of bicyclists is associated with multiple factors such as transportation infrastructure (Monsere et al., 2014), surface condition (Calvey, Shackleton, Taylor, & Llewellyn, 2015), and even bicycle ergonomics (Ayachi, Dorey, & Guastavino, 2015). From a road user standpoint, bicyclists found protected bicycle facilities with physical buffers to offer greater PLOC than standard bike lanes (McNeil et al., 2015), bicyclists with near miss and collision experiences were found to have lower PLOC (Sanders, 2015), and bicyclists on facilities that had low traffic volumes were found to have higher PLOC (Winters et al., 2011).

The perception of comfort and safety influences the decision to bicycle and the frequency of bicycling (Dill & McNeil, 2013). This is of special importance among women bicyclists as several studies showed that women's perceptions of comfort and safety are critical elements in their tendency to bicycle (Emond, Tang, & Handy, 2009; Krizek, Johnson, & Tilahun, 2005; Tilahun, Levinson, & Krizek, 2007). Perceived safety greatly influences the attractiveness of a facility, particularly for infrequent and potential bicyclists (Sanders, 2013). Even for experienced bicyclists, perception of safety has been found to be one of the most influential factors in determining the frequency of bicycling (Damant-Sirois & El-Geneidy, 2015). While improving perceived comfort and safety is an important condition for increasing levels of bicycling, no research has yet comprehensively identified the constructs of bicyclist perceived comfort based on bicyclists' characteristics.

3. Research objectives

As identified in the literature, while bicyclist behavioral norms influence their behavioral response, this interaction has yet to be holistically evaluated, especially with regard to PLOC. This study is the first of its kind to investigate the relationships among bicyclists' characteristics, PLOC, safety beliefs, and their safe/risky responses in a particular scenario: the presence of a truck in the adjacent lane as a potential hazard. With regard to previous efforts and in order to enrich the understanding of bicyclist behavior, in the present study, self-reported behavior of distracted bicycling, subjective norms regarding road user behavior, and bicycling habits were developed as latent variables; level of experience, and history of incidents were captured as observed variables; and their aggregate effects on PLOC were studied. Fig. 1 shows the study framework that employed Structural Equation Modeling (SEM). SEM is a general statistical methodology and a widely accepted technique to study the relationship between attitudes, intentions, perceptions, and behavior.

4. Method

4.1. Study design and survey

Online surveys have been widely adopted to study road users' behavior (e.g., Hassan & Abdel-Aty, 2011; McNeil et al., 2015; Neill, Hurwitz, & Olsen, 2016; Sanders, 2013). To achieve the objectives of the present study, literature regarding bicyclist behavior surveys was carefully evaluated and questions were primarily developed in accordance with previous work (e.g., Dill, McNeil, & Monsere, 2016; Jannat, 2014; Twisk, Vlakveld, & Commandeur, 2007). Qualtrics was used to develop the online survey. Survey questions were revised through an iterative process. Initially, the developed survey was alpha tested by members of the research team, then beta tested with selected students from the Transportation Graduate Program at Oregon State University. To conduct the alpha and beta tests, a temporary link was generated to direct participants to the online survey. The alpha and beta testing resulted in improvements to the logic and sequence of the survey questions and the correction of grammatical errors and typos thereby improving the final distributed survey. Recommendations from the literature were considered to validate the final survey design and reduce survey errors (Dillman, Smyth, & Melani, 2009). The final survey consisted of four sections: (a) demographic information, (b) bicycling characteristics among survey participants such as safety beliefs and habits, (c) participants' PLOC under different configurations of ambient traffic and engineering treatments, and (d) bicyclist predictive response to the presence of a truck in the adjacent lane near an urban loading zone.

Fig. 2 shows the scenario, generated in Google SketchUp 2017 software, from the online survey used to investigate PLOC when a truck was present in the adjacent lane near a loading zone. Handlebars of the bicycle were pictured such that participants of the survey had a first-person view of the environment. Bicycle was located at the center of the bicycle lane and in the blind spot of the truck. The roadway cross-section considered in the scenario included two 12-ft travel lanes with 6-ft bicycle lanes in each direction. An 8-ft parking lane interrupted by an on-street loading zone was created in one direction to allow for bicycle-truck interactions. Two types of engineering treatments, pavement marking and signage, were included in the final design to provide a better perception of bicyclist positioning and ambient characteristics. Colored pavement within a bicycle lane increases visibility of the facility, identifies potential areas of conflict, and reinforces priority to bicyclists in the conflict areas (NACTO, 2011). In the final design, solid green pavement marking was applied on the conflict area. Additionally, a generic warning sign was placed upstream of the loading zone to inform bicyclists of a potential hazard on the road (FHWA, 2009). Survey participants were first asked to rate their PLOC for bicycling under the illustrated scenario on a 10-point rating scale, from very uncomfortable (0) to very comfortable (10). Responses were constrained to integers, as in common ranking scales. This approach is consistent with recent research that suggests no meaningful difference between continuous versus categorical responses (Bosch, Revilla, DeCastellarnau, & Weber, 2018; Roster, Lucianetti, & Albaum, 2015). Participants were subsequently asked to report their most probable reaction given the depicted situation. In this study, "Brake immediately" and "Stop pedaling" were considered as safe responses, while the other choices were categorized as risky responses. "Other" responses were evaluated on a case by case basis and were categorized as either safe or risky responses.

4.2. Participants

This study was initially aimed at investigating bicycling behavior among the general population of Oregon, with two lenient inclusion criteria: (1) between the ages of 18 and 75 years old, and (2) had bicycled in the past year. Thus, 10,000 random residential addresses across Oregon were purchased through a third-party company. Postcards were designed, printed, and mailed to these addresses, providing residents with a reusable link and a unique household ID to participate in the online survey. Within the first two months, 182 responses were collected (1.82% response rate), which limited a comprehensive analysis of bicyclist behavior, so, additional potential participants were contacted through various email listservs. These listservs were obtained through researcher connections with regional and national bicycling clubs (e.g., Corvallis BikePed Google Group) and other research institutes (e.g., UCLA Institute of Transportation Studies). Ultimately, the online survey was completed by 414 participants. Collected data were then initially screened to remove partially completed responses and univariate and multivariate outlier tests were conducted to remove significant outliers based on standardized values and skewness and Kurtosis statistics. The final dataset was consisted of 342 participants, including 127 women (M_{age} = 39.57,

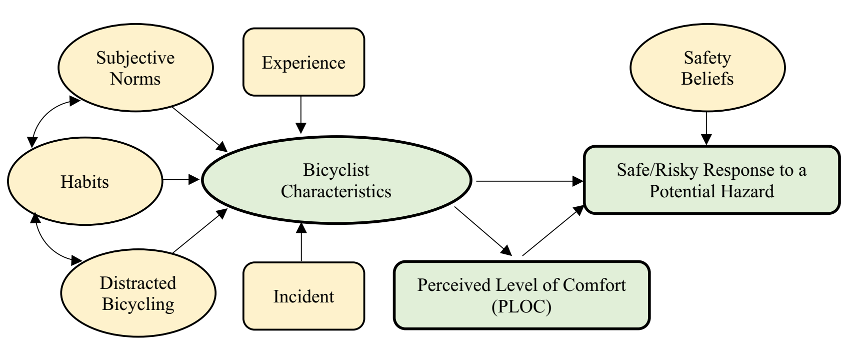

Fig. 1. SEM Application to Study Bicyclists' PLOC and Safe/Risky Response to a Potential Hazard.

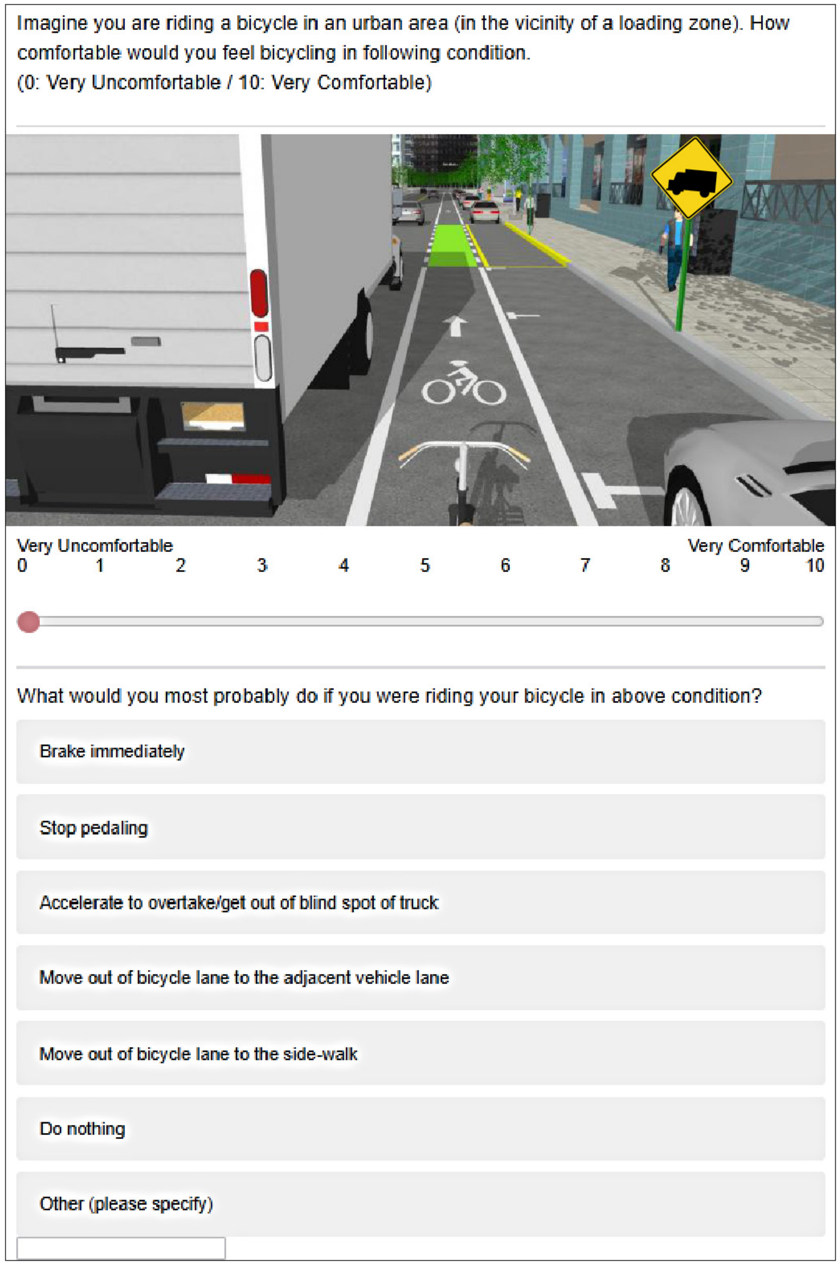

Fig. 2. Screenshot from Online Survey with Studied Scenario.

SD_{age} = 13.75) and 215 men (M_{age} = 44.79, SD_{age} = 15.20). Table 1 presents a descriptive summary of the sample demographics.

A descriptive summary of demographics indicated that the final sample included a large percentage of white male bicyclists. While no intended group of bicyclists was considered for this study, this sample seems to characterize the bicyclist population in the United States fairly well. Data from the 2018 benchmarking report for biking and walking in U.S. (League, 2018) show that while women represent 50.8% of the population of United States, they only represent 30.3% of all bicycling trips. Additionally, while about 28% of the U.S. population is non-White, people of color account for only about 19% of bicycle trips. Of course, discrepancies were also observed between the final sample and the bicyclist population in the United States. For instance, the highest proportion of reported income in the final sample was between $100,000 and $200,000. However, data from the aforementioned report suggest that bicycling is much more common as a means of commuting to work for those with lower income levels.

4.3. Statistical analysis

SEM is a series of statistical methods that allow for the analysis of complex relationships between one or more independent variables and one or more dependent variables. It can be viewed as a combination of factor analysis and regression or path analysis. SEM can encompass observed or measured variables (also known as manifest variables) as well as theoretical constructs that are not directly measured (also known as latent variables). SEM is often visualized by a graphical path diagram in which observed variables are represented by rectangle boxes and latent variables are represented by ellipses. Single headed arrows are used to define causal relationships and double headed arrows indicate

Table 1
Descriptive Summary of Sample Demographics.

Demographic	Category	No. of Participants	Percentage of Participants (%)
Age	18–24 years	24	7.02
	25–34 years	114	33.33
	35–44 years	54	15.79
	45–54 years	61	17.84
	55–59 years	22	6.43
	60–64 years	29	8.48
	65–75 years	38	11.11
Gender	Female	127	37.13
	Male	215	62.87
Education	Some high school or less	1	0.29
	High school diploma or GED	7	2.05
	Some college	16	4.68
	Trade/vocational school	10	2.92
	Associate degree	10	2.92
	Four-year degree	107	31.29
	Master's degree	153	44.74
	PhD degree	34	9.94
	Prefer not to answer	4	1.17
Race	American Indian or Alaska Native	1	0.29
	Asian	21	6.14
	Black or African American	2	0.58
	Hispanic or Latino/a	9	2.63
	White or Caucasian	280	81.87
	Other	20	5.85
	Prefer not to answer	9	2.63
Income	<$25,000	43	12.57
	$25,000 to <$50,000	46	13.45
	$50,000 to <$75,000	58	16.96
	$75,000 to <$100,000	54	15.79
	$100,000 to <$200,000	87	25.44
	≥$200,000	25	7.31
	Prefer not to answer	29	8.48

covariance (Hox & Bechger, 1998). The advantages of using SEM include: (1) complex relationships can be analyzed, (2) all coefficients in the model are estimated simultaneously, (3) multicollinearity is accounted for, and (4) measurement error is eliminated when latent variables are included (Dion, 2008; Hassan & Abdel-Aty, 2011).

SEM has been broadly employed to model road user behavior (e.g., Hamdar, Mahmassani, & Chen, 2008; Li, Gkritza, & Albrecht, 2014; Sanders, 2013; Shi, Bai, Tao, & Atchley, 2011; Sukor, Tarigan, & Fujii, 2017). In this study, SEM was used to systematically investigate the construct of bicycling PLOC and simultaneously analyze bicyclists' responses to the presence of a truck in a dense urban environment by developing four latent variables from survey questions representing bicyclist characteristics and safety beliefs:

1) Distracted bicycling: representing the reported frequency of performing secondary tasks while bicycling.
2) Subjective norms: representing attitudes about road users' behavior.
3) Habits: representing bicyclists' regular tendencies, and
4) Safety beliefs: representing beliefs about the acceptability of certain risky behaviors while bicycling.

Table 2 shows definitions and summary statistics for the selected variables in the final model. SEM was applied in this study using R software (version 3.3.1) package lavaan (Rosseel, 2012). Linearity and normality assumptions were checked for all the variables in the final SEM.

5. Results

Fig. 3 depicts a graphical representation of the final SEM with the standardized path coefficients (loading factors), and Table 3 shows the SEM estimation results. The final structure was achieved through an iterative modeling process. Several SEM structures were investigated and the one that was found to be the most descriptive of identified conceptual objectives and demonstrated the best statistical fit of the data was chosen. There are two models within the larger model of the final SEM: one to examine the construct of PLOC, and the other to examine reported safe/risky responses to the presence of a potential hazard.

Two of the widely reported Goodness-of-Fit indices used in SEM analysis are Root Mean Square Error of Approximation (RMSEA) and Standardized Root Mean Square Residual (SRMR). According to Hooper, Coughlan, and Mullen (2008), a value less than 0.08 for these parameters could indicate an acceptable fit. The results of SEM estimation suggest a value equal to 0.076 for RMSEA and 0.079 for SRMR, both of which confirm an acceptable fit for the final structure. Akaike Information Criterion (AIC) is also reported in Table 3. However, because AIC is not confined to a 0–1 scale, cut-offs are not suggested but the model that produces the lowest value is considered superior.

To evaluate PLOC, three latent variables were constructed and their direct effect on PLOC was evaluated through simultaneous regression models. All latent variables were unobserved, unit-less constructs. As such, to define a unit of measurement, a non-zero coefficient was assigned to each of the latent variables as an indicator. These reference variables were given the value of 1 and are shown as estimated coefficients in Table 3.

The latent variable "Distracted Bicycling" had the largest negative impact on PLOC (loading factor = −0.235, *t*-value = −2.634). "Distracted Bicycling" was developed from three observed variables that captured the frequency of performing secondary tasks while bicycling. These observed variables were coded such that a higher value represented more frequent distracted bicycling. Talking by phone and texting had positive impacts in constructing "Distracted Bicycling" as a latent variable (*DB2* loading factor = 0.651 and *DB3* loading factor = 0.719). Listening to music was also positively effective but to a lesser extent (*DB1* loading factor = 0.254).

The latent variable "Habits", had the largest positive impact on PLOC (loading factor = 0.130, *t*-value = 2.155) among all latent variables. "Habits" was constructed from four observed factors. According to the SEM results, using a bicycle predominantly for the *purpose* of commuting to work/school (loading factor = 0.921), as well as having a higher *frequency* of bicycling (loading factor = 0.517), shorter *duration* of bicycling (loading factor = 0.431), and *exposure* to a similar condition in an urban environment (loading factor = 0.161) had positive impacts on the construct of "Habits" as a latent variable.

The latent variable "Subjective Norms" seemed to have a positive impact on PLOC (loading factor = 0.098, *t*-value = 1.668), though this did not quite reach statistical significance. This latent variable was developed with four observed factors, intended to capture participants' perceived social norms about the behavior of road users. The SEM estimation results showed that participants' ratings regarding bicyclists' lawfulness (*SN3* loading factor = 0.817) and predictability (*SN4* loading factor = 0.762) had higher impacts in constructing subjective norms than ratings regarding drivers' lawfulness (*SN1* loading factor = 0.549) and predictability (*SN2* loading factor = 0.564).

Covariance estimates among these developed latent variables showed that "Habits" and "Distracted Bicycling" were directly correlated (loading factor = 0.233), while "Habits" and "Subjective

Table 2
Variable Descriptions and Summary Statistics.

Variable	Variable description	Response frequency				
Distracted Bicycling	During the past year, as a bicyclist, have you ridden a bicycle under the following circumstances? (*latent variable*)					
				Not at all	Sometimes	Frequently
DB1	Listening to music (using headphones)			75.4%	12.9%	11.7%
DB2	Talking on the phone			80.1%	18.1%	0.9%
DB3	Texting			84.2%	14.9%	0.9%
Subjective Norms	To what extent do you agree or disagree with the following statements? (*latent variable*)					
		Strongly Disagree	Disagree	Neutral[a]	Agree	Strongly agree
SN1	Most drivers follow the rules of the road	8.5%	23.1%	13.2%	50.6%	4.7%
SN2	Most drivers are predictable	5.3%	25.7%	16.7%	48.8%	3.5%
SN3	Most bicyclists follow the rules of the road	8.2%	26.9%	26.0%	37.7%	1.2%
SN4	Most bicyclists are predictable	7.9%	28.1%	28.7%	33.9%	1.5%
Safety Beliefs	While riding a bicycle it is acceptable to (*latent variable*)					
		Strongly Disagree	Disagree	Neutral[a]	Agree	Strongly agree
SB1	Make turns without signaling	23.1%	40.9%	19.9%	11.7%	4.4%
SB2	Run a red light with no traffic in sight	21.3%	23.7%	18.1%	26.0%	10.8%
SB3	Ride on sidewalk	11.7%	26.3%	25.4%	28.6%	8.0%
SB4	Not wear a helmet	25.4%	22.2%	25.7%	17.0%	9.7%
Habits	Bicycling habits (*latent variable*)					
		Monthly	Weekly	Daily		
Frequency	How often do you usually ride a bicycle?	15.2%	37.4%	47.4%		
		More than 20 minutes	20 minutes or less			
Duration	How long do you usually ride a bicycle on a typical trip?	58.5%	41.5%			
		Non-commuting	Commuting to work/school			
Purpose	What is your primary purpose for riding a bicycle?	48.2%	51.8%			
		No	Yes			
Exposure	Have you ever ridden a bicycle in a central business district or a busy downtown?	9.4%	90.6%			
		No	Yes			
Incident	Have you ever been involved in an accident/incident while riding a bicycle?	52.6%	47.4%			
Safe/Risky Response to a Potential Hazard		Risky	Safe			
	Bicyclist response to presence of a truck on adjacent lane (Fig. 2)	36.8%	63.2%			
PLOC	Perceived Level of Comfort	Mean: 4.50 | SD: 2.19				
Experience	How do you describe your experience as a bicyclist?	Mean: 8.10 | SD: 2.04				

[a] Worded as "Neither agree nor disagree" in the survey.

Norms" were inversely correlated (loading factor = −0.106). This means that people who stated a higher *frequency* of bicycling, had more *exposure* to downtown bicycling, had shorter a bicycling *duration*, and bicycled for the *purpose* of commuting to work/school were more likely to report engaging in distracted bicycling and were less likely to perceive other road users as lawful and predictable.

In addition to the latent variables, *experience* as an observed variable was included in PLOC model. SEM estimation results showed that being an experienced bicyclist significantly increased PLOC for bicycling next to a truck (loading factor = 0.236, *t*-value = 4.581).

Bicyclists' reported safe/risky response to the presence of a potential hazard on the road was examined with one latent variable and three observed variables. The latent variable "Safety Beliefs" had a negative impact on the safe/risky response of bicyclists to presence of truck in the adjacent lane (loading factor = −0.137, *t*-value = −2.070). "Safety Beliefs" was developed from four observed variables that covered a wide range of safety issues while bicycling. Participants' beliefs about the acceptability of making turns without signaling (*SB1* loading factor = 0.612), not wearing a helmet (*SB4* loading factor = 0.596), running a red light with no traffic in sight (*SB2* loading factor = 0.553), and riding on the sidewalk (*SB3* loading factor = 0.457) were all effective in constructing bicycling "Safety Beliefs." According to the SEM estimation results, having a history of *incidents* while riding a bicycle (loading factor = −0.147, *t*-value = −2.770) negatively influenced bicyclists' safe response to the presence of a potential hazard on the road while, having a higher PLOC (loading factor = 0.119, *t*-value = 2.229) positively influenced bicyclists' safe response.

Finally, it is crucial to differentiate the theoretical importance and the statistical significance of "Subjective Norms" in the final SEM. The effects of this variable was not statistically significant with a 95% confidence interval (*p*-value = 0.096) but it was included in the final model, based on its theoretical importance. Previous studies have suggested that subjective norms, such as those included in this study and other bicyclist characteristics could influence bicyclist perception of comfort and safety (Dill et al., 2016; Piatkowski et al., 2017; Twisk et al., 2007). However, the magnitude and direction of this influence have not been evaluated. As such, to enrich the understanding of bicyclist behavior, this variable was retained in the final SEM.

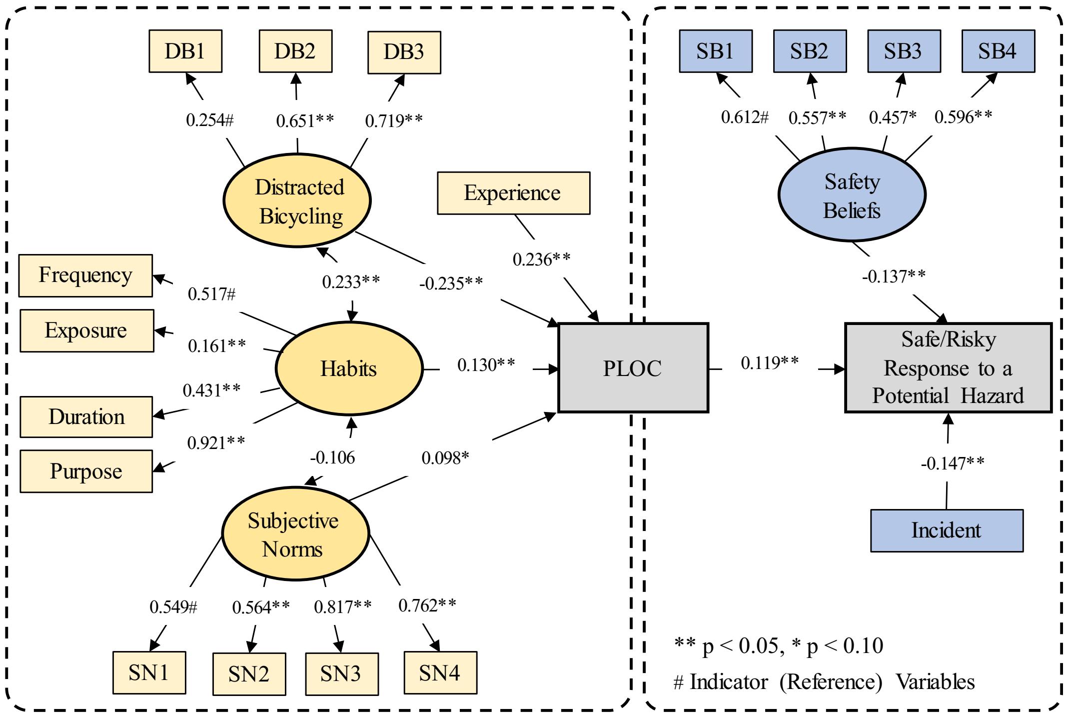

Fig. 3. SEM path diagram with standardized coefficients.

Table 3
SEM estimation results.

Path	Estimated coefficient	Standardized coefficient	Standard Error	*t*-Statistics	*p*-value
Latent Variables					
Distracted Bicycling					
DB1 ← Distracted Bicycling	1.000	0.254			
DB2 ← Distracted Bicycling	1.594	0.651	0.438	3.641	0.000
DB3 ← Distracted Bicycling	1.736	0.719	0.483	3.593	0.000
Subjective Norms					
SN1 ← Subjective Norms	1.000	0.549			
SN2 ← Subjective Norms	0.954	0.564	0.125	7.650	0.000
SN3 ← Subjective Norms	1.355	0.817	0.149	9.072	0.000
SN4 ← Subjective Norms	1.245	0.762	0.138	9.003	0.000
Habits					
Frequency ← Habits	1.000	0.517			
Duration ← Habits	0.570	0.431	0.090	6.361	0.000
Purpose ← Habits	1.233	0.921	0.209	5.903	0.000
Exposure ← Habits	0.124	0.161	0.046	2.680	0.007
Safety Beliefs					
SB1 ← Safety Beliefs	1.000	0.612			
SB2 ← Safety Beliefs	1.113	0.557	0.167	6.650	0.000
SB3 ← Safety Beliefs	0.792	0.457	0.134	5.899	0.000
SB4 ← Safety Beliefs	1.164	0.596	0.170	6.830	0.000
Regressions on PLOC					
PLOC ← Distracted Bicycling	−2.967	−0.235	1.127	−2.634	0.008
PLOC ← Subjective Norms	0.354	0.098	0.212	1.668	0.095
PLOC ← Habits	0.757	0.130	0.351	2.155	0.031
PLOC ← Experience	0.254	0.236	0.055	4.581	0.000
Regressions on Reported Response					
Reported Response ← PLOC	0.026	0.119	0.012	2.229	0.026
Reported Response ← Incident	−0.141	−0.147	0.051	−2.770	0.006
Reported Response ← Safety Beliefs	−0.099	−0.137	0.048	−2.070	0.038
Covariance					
Habits ↔ Distracted Bicycling	0.015	0.233	0.007	2.302	0.021
Subjective Norms ↔ Habits	−0.024	−0.106	0.015	−1.558	0.119
Goodness-of-Fit					
Root Mean Square Error of Approximation (RMSEA)		Point Estimate		0.076	
		90% Confidence Interval		0.068	0.085
Standardized Root Mean Square Residual (SRMR)		0.079			
Akaike Information Criterion (AIC)		12705.689			

6. Discussion

Though bicycle-truck conflicts in dense urban environments could create severe safety consequences, bicyclist behavior while encountering trucks in close proximity to urban loading zones has yet to be analyzed robustly. This study attempted to shed further light on aspects that influence bicyclists' responses to the aforementioned conflict, notably investigating the construct and role of PLOC. "Distracted Bicycling" inversely affected PLOC, indicating that participants who said that they engaged more frequently in secondary tasks while bicycling reported lower levels of PLOC and chose a risky rather than a safe response to the presence of a potential hazard on the road. For instance, while 21.4% of participants who chose risky responses reported occasionally talking by phone during bicycling, only 11.1% who chose safe responses did so.

"Subjective Norms" seemed to positively affect PLOC. In fact, participants who believed that drivers and bicyclists follow rules of the road and perceived those road users as predictable stated higher PLOC values for bicycling next to a truck in the adjacent lane and chose a safe rather than a risky response. For participants who reported safe behavior, only 25.0% and 35.6% disagreed or strongly disagreed with driver and bicyclist lawfulness, and only 28.7% and 35.2% disagreed or strongly disagreed with driver and bicyclist predictability.

The observed factors contributing to bicycling "Habits" showed that participants who bicycled primarily for the *purpose* of commuting, made shorter trips, had a higher *frequency* of bicycling, and had greater *exposure* to similar situations reported a higher PLOC, and chose a safe response when bicycling next to a truck in the adjacent lane. This is an interesting finding suggesting that familiarity with the immediate environment could improve bicycling comfort and increase safe behavior. This is also in line with the estimated effect of *experience*, as those who reported a higher level of experience, also reported higher PLOC values and chose a safe response.

The most important finding revolves around the observed relationship between PLOC and bicyclists' responses to the presence of a potential hazard on the road. Well established theories in social sciences have shown that certain attitudes and perceptions are predictive of people's behavior. For example, the theory of planned behavior relates the performance of a behavior to a joint function of intentions and perceived behavioral control (Ajzen, 1991). The findings of the present study show that the PLOC does have a significant impact on bicyclist behavior, as participants with higher PLOC more frequently chose a safe rather than a risky response. In fact, those who chose a safe behavioral response, reported a higher 12.8% PLOC value, versus those who chose a risky behavioral response. This supports the notion that one way to improve bicyclist safety would be to create an environment that increases PLOC for bicyclists.

While SEM made it possible to investigate the relationship between PLOC and safe/risky responses, it also allowed for the simultaneous development of bicyclist safe/risky response to presence of a truck as a theoretical construct. The SEM estimation results showed that people with a history of previous *incidents* were more prone to risky behavior during a bicycle-truck interaction. For participants who chose a risky behavior, 56.3% reported having been involved in a past incident while bicycling.

Finally, "Safety Beliefs" showed that participants who had a more lenient approach toward the acceptability of performing risky behaviors while riding a bicycle, more frequently reported a risky response to the presence of a truck in the adjacent lane. For example, while 51.9% of participants who chose a safe response disagreed or strongly disagreed with acceptability of not using a helmet while bicycling, this rate was only 40.4% for participants who chose risky behaviors. People who accept risky behaviors while bicycling (e.g., riding on sidewalk) are more likely to choose a risky response to the presence of a truck (e.g., move out of the bicycle lane to the sidewalk).

7. Summary and conclusion

While active transportation policies are largely investing in bicycling as an environmentally friendly alternative to motorized vehicle travel, safety concerns have negatively influenced bicycling growth. Perception of comfort and safety is one of the most important determinants of people's bicycling frequency. Though bicycling PLOC and bicycling safety have been previously examined, critical gaps exist in the literature. Specifically, to date, no study has looked into the PLOC construct with respect to bicyclist characteristics, and no research has inspected the influence of PLOC on bicyclist behavior.

To address these gaps in the literature, the present paper proposed and examined underlying components of the PLOC construct for bicycling and evaluated bicyclist safe/risky response to the presence of a truck in the adjacent lane near an urban loading zone via an online survey. Concurrently with the development of these two variables, application of the SEM technique made it possible to investigate the influence of PLOC on bicyclist response.

The PLOC construct was evaluated based on three latent variables. Participants who stated that they engaged in more frequent "Distracted Bicycling" reported lower levels of PLOC. For "Subjective Norms," those who expressed stronger agreement that road users are lawful and predictable reported higher PLOC. Similarly, more *experience* as a bicyclist increased PLOC. Finally, participants who bicycled for the *purpose* of commuting, made shorter *duration* trips, had a higher *frequency* of bicycling, and had more *exposure* to downtown bicycling reported higher PLOC.

Findings showed that higher PLOC was significantly associated with the choice of a safe rather than a risky response to the presence of a potential hazard, suggesting that a way to improve bicyclist safety would be to build an environment that could increase the perception of comfort for bicyclists. Additionally, the choice of a safe rather than a risky response was inversely impacted by a history of *incidents* while bicycling. "Safety Beliefs" directly influenced bicyclists' safe/risky responses to the presence of a potential hazard on the road, as people who agreed with the acceptability of performing risky behaviors while riding a bicycle, more frequently chose a risky response.

While this study employed a relatively extensive survey, large sample size, and widely accepted statistical methodology, it is still limited in a few ways. This study utilized stated preferences. While this is an acceptable starting point, the findings of the present study need to be validated with revealed preferences, such as data from bicycling simulation experiments (Horne, Abadi, & Hurwitz, 2018; Hurwitz, Abadi, McCormack, Goodchild, & Sheth, 2018). Specifically, this study investigated bicyclist behavior in the presence of a truck, but it should be noted that not every aspect of bicycle-truck interactions could be obtained from a stated preference survey. Additionally, this study only looked at bicycle-truck interactions in a distinctive built environment. Considering other types of vehicles, bicycle facilities, and engineering treatments could shed further light on bicyclist behavior near urban loading zones. The final sample accumulated responses from both postcard recruitment and a convenience sample. This happened to obtain greater power in the statistical analysis. However, different sampling methods might result in different responses. A future study should investigate the reliability of these two sampling techniques. Finally, similar to any other human behavior, explaining bicycling

PLOC and bicyclists' safe responses to the presence of a potential hazard on the road in all their complexity is a difficult task. Future research is needed to investigate these complex constructs from broad perspectives that take into account bicyclists' beliefs, attitudes, intentions, and behaviors.

More broadly, PLOC could play an important role in strategic bicycle planning, bicycle infrastructure design, characteristics of urban built-in environments, and traffic operation and control. Although the present study attempted to shed light on the construct of PLOC, the association between PLOC and the aforementioned topics warrants additional study.

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