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Examining the relationship between perceived bikeability, cycling preferences and cycling distance

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ABSTRACT

Understanding cycling behaviour is crucial for transport sustainability and individual health. Existing research has primarily focused on objectively measured bikeability using cross-sectional data, which are unable to assess within-person effects over time. Using longitudinal data from the Netherlands Mobility Panel, this paper applies a Cross-Lagged Panel Model and a Random-Intercept Cross-Lagged Panel Model to analyse the causal relationship between perceived bikeability, cycling preferences and cycling distance. The results show that individuals' cycling preferences and distance are relatively stable over time with positive autoregressive effects. Higher perceived bikeability and cycling distance directly encourage individual cycling distances and preferences separately in the subsequent year, with cross-lagged effects. For between-person effects, people with higher perceived bikeability generally have stronger cycling preferences and cycle longer distances. The Random-Intercept Cross-Lagged Panel Model provides a superior model fit to separate within-person from between-person effects. These findings are valuable for promoting cycling.

1. Introduction

As an environmentally friendly mode of transport, cycling has multiple potential benefits (Liu et al., 2021). At the network level, cycling can reduce traffic congestion, air pollution, and energy consumption when used as an alternative to motorised modes of transport, such as the private car (Frank et al., 2010; Maizlish et al., 2017). At the individual level, cycling can also provide health benefits by preventing or reducing several chronic diseases through increased activity levels (Ton et al., 2019), as well as being associated with higher travel satisfaction (De Vos et al., 2016). Analysing cycling behaviour can help to understand the factors that motivate people to frequently cycle. Effective policies can then be designed to encourage its use, and increase its modal share (Sun et al., 2020).

Many studies have analysed objectively measured bikeability, as well as the relationship between cycling preferences and cycling behaviour. However, given that perceived and objectively measured bikeability have different effects on cycling behaviours (Gan et al., 2021; Kellstedt et al., 2021; Ma & Dill, 2016), it is not enough to provide merely sufficient physical infrastructure to improve bikeability. It is also necessary to enhance the perception of cycling infrastructure in order to encourage more people to cycle.

Existing studies rely heavily on cross-sectional survey data, which can only evaluate between-person effects (relationships between different individuals at the same time point) and may present challenges in making causal inferences due to the lack of a temporal

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dimension (Dai et al., 2020). Only longitudinal study designs can take into account for the temporal sequence and examine the within-person changes (changes over time for the same person) (Rahman, 2023) for the purpose of making causal inferences. However, their use in studies of cycling behaviour is very limited.

To fill the research gaps, we intend to analyse the causal relationship between perceived bikeability, cycling preferences and cycling behaviour, where e-bikes are not included in this study. Cross-lagged panel models (CLPM) and Random-Intercept Cross-Lagged Panel Model (RI-CLPM) will be applied to examine the causal relationships between variables based on longitudinal data. Specifically, we aim to address two research questions:

1) How do perceived bikeability, preferences and cycling interrelate with each other over time?
2) Which method is better for analysing the within-person effects over time based on longitudinal data?

The present study contributes twofold to the literature. Empirically, it enriches the understanding of the causal relationship between perceived bikeability, cycling preferences and travel behaviour based on longitudinal data. The findings indicate that the perceived bikeability directly encourages individual cycling distances in the following year with cross-lagged effects. By revealing the refined relationships, we offer implications for policy makers to encourage cycling use by improving their perceived bikeability. Methodologically, the RI-CLPM method is examined to be better distinguish between- and within-person effects.

The rest of the paper is organised as follows. Section 2 reviews the existing research, followed by the description of the data and variables used in Section 3. Section 4 conceptualises the methodology used. The results of the model estimation are presented and discussed in Section 5. At the end, Section 6 summarises the main findings and draws policy implications.

2. Literature review

This section provides an overview of the research on perceived bikeability, cycling preferences and cycling behaviour. Methods for analysing longitudinal data are also reviewed.

Cycling behaviour has been analysed for a long time. These studies mainly focused on determinants of cycling, such as socio-demographics, preference, and built environment (Maldonado-Hinarejos et al., 2014; Schneider et al., 2023). Structural equation model (Vallejo-Borda et al., 2020), multinomial logit model (Zhao et al., 2018) and ordinary least square analysis (Schneider et al., 2023) have been adopted to quantify their relationship based on cross-sectional data. Cycling as a commute mode is significantly positively correlated with being a man, student, and young, and having a low median income (Ryley, 2006; Vandenbulcke et al., 2011). Cycling duration and distance are influenced by positive preferences towards cycling (Gao et al., 2019; Haustein and Møller, 2016) and landscape design (Etminani-Ghasrodashti et al., 2018). Bikeability, which is based on the design of cycling infrastructure that prioritises comfort, directness, coherence, attractiveness, and safety (Bach et al., 2006), has also been used as a variable to explore its effect on cycling behaviour. Higher bikeability of routes (Beecham et al., 2023) and bikeability of area (Codina et al., 2022) were both found to be positively associated with the number of observed cycling trips and the likelihood of using a bicycle. Arellana et al. (2020) also proposed a direct demand model to prioritise bicycle infrastructure investments based on the estimation of bikeability indexes and expected flows of cyclists.

However, inconsistencies have also been examined in the literature, where higher levels of cycling were not associated with objective measures of proximity to off-road paths and cycle lanes (Akar and Clifton, 2009). Kellstedt et al. (2021) found that students' perceptions of bikeability were lower than objective assessments of routes. This may be explained by the difference between perceived and objectively measured bikeability due to the individual preferences, capabilities and the knowledge of the transport system (Ma & Dill, 2016; Pot et al., 2021; Schwanen & Mokhtarian, 2005). Considering a resident who is used to travelling by car and has never considered cycling, a new dedicated cycle lane connecting home and park increases bikeability, but does not change the perceived bikeability for that individual.

Perceptions of cycling were categorised into perceptions of benefits, barriers, safety, cycle routes, cyclists, transport options, and parental perceptions (Willis et al., 2015). Kang et al. (2019) used thematic analysis to identify the attributes of perceived bikeability, including physical environment, supportive community system, cultural influence, and conflicts over cycling. Perceived cycling environment (Vallejo-Borda et al., 2020) was further modified as an explanatory variable to explore the relationship with future cycling preferences and cycling frequency. A strong association between cycling distance and perceived bikeability was found a Nanjing case study based on cross-sectional data in 2018 (Gan et al., 2021). Zhao et al. (2018) investigated that certain perceptions, such as perceived cycling safety and pleasure, promote bicycle use and positive preferences (Blitz, 2021). Accessibility and amenities were crucial in the development of recreational cycling, as they mediate components of perceived value (Aizat et al., 2023). For some demographic groups, such as the elderly and women, the perceived effectiveness of current cycling initiatives was found to be lower (Jahanshahi et al., 2023). Perceived accessibility of dock less bike sharing system (DBS) (Chen et al., 2022) notably increases the choice of DBS–metro integration (Guo and He, 2021).

The cross-sectional data makes it difficult to disentangle causal effects and correlational relationships. The correlational relationships may provide an incomplete picture, making it difficult to derive sound policies. Existing research based on the longitudinal data to make causal inferences has mostly been modelled using methods such as latent transition models (LTA) (Olde Kalter et al., 2020), Cross-lagged panel models (CLPM) (Kroesen et al., 2017) and Random-Intercept Cross-Lagged Panel Models (RI-CLPM) (Gassiot Melian et al., 2016). Kroesen et al. (2017) recognised that people with consonant attitude-behaviour patterns are more stable than dissonant patterns and that effects from attitudes to behaviour are smaller than vice versa using CLPM. LTA was selected to determine how attitudes towards car use and ownership change over time and how these changes affect car use (Olde Kalter et al., 2020). De Haas et al. (2022) uses RI-CLPM to examine not only the relationship between health and active travel, but also the change of trip rates with different travel modes. RI-CLPM has also been used to estimate within-person and between-person effects (Faber et al., 2023). Tao (2024) conduct that the use of public transport and bicycles by place of residence had a one-year lagged effect on mode preference. No previous study has yet compared the use of CLPM and RI-CLPM for estimating the causal relationship between perceived bikeability, and travel behaviour on between- and within-person approaches. Therefore, it is necessary to use both methods to analyse whether there are differences between the two models (Hihara et al., 2021).

3. Data

3.1. Sample selection

We use panel data from the Netherlands Mobility Panel (MPN), which consists of a 3-day travel diary (Hoogendoorn-Lanser et al., 2015). The MPN has been conducted since 2013 which surveys approximately 6,000 individuals aged 12 and older each year. Respondents are randomly selected and recruited nationwide. The main objective aims to monitor dynamic trends in the travel behaviour of households and individuals. The longitudinal nature of MPN allows this study to examine the relationship between cycling preferences, perceived bikeability and travel behaviour over time. A detailed description of the survey design, sampling and procedures can be found in (Hoogendoorn-Lanser et al., 2015).

We use four waves of data from the MPN, covering the years 2013 to 2016. Respondents who failed to finish the 3-day travel diary were removed from the study. The total sample consists of 8,706 individuals, of whom 1,204 participated in all four waves. The final sample consisted of 1,203 respondents. There may be attrition bias when analysing participants who responded to all four waves. When comparing the means of cycling preferences, perceived bikeability and travel behaviour of the survey respondents (N = 1,203) with the sample respondents (N = 8,706), we found no significant differences, suggesting that there is no serious problem of attrition bias (Table 1).

3.2. Variable specification

Perceived bikeability was measured by asking respondents if their neighbourhood had good cycling infrastructure. Their responses were coded on a 5-point scale ranging from 1 (strongly disagree) to 5 (strongly agree) (Blitz, 2021; Chen et al., 2022; Zhao et al., 2018; Mehdizadeh & Kroesen, 2025). The question is very general but has two advantages: It summarizes the overall subjective perception with the cycling infrastructure in their neighbourhood, and provides an overall understanding of the perceived bikeability without asking multiple questions concerning the five factors (e.g., asking separately about whether the cycling infrastructure is good for comfort, directness, coherence, attractiveness, and safety) that may distort the results. For instance, if a person has to make a small detour because of the low cycling directness, but the cycling infrastructure can provide a comfortable and safe riding experience, the perceived bikeability could be high. The preferred mode was asked each year for eight different purposes, including sport, day trip, going out, visiting other people, shopping, food shopping, school, business and commuting. Regarding travel mode preferences, respondents are asked about their preferred transport mode for eight different purposes, regardless of the actual frequency with which they make the trip. Cycling preferences were calculated by the ratio between the frequency of cycling as the preferred mode and the total number of purposes, ranging from 0 to 1 (Mehdizadeh & Kroesen, 2025; Olde Kalter et al., 2021; Tao, 2024), thereby capturing the variance in their travel preferences. We operationalise travel behaviour as the average distance cycled in a three-day travel diary, as cycling distances are collected for the same three days each year.

For socio-economic characteristics at both individual and household level, we include gender, household income, reimbursement for cycling and bicycle ownership. Gender, reimbursement for cycling and bicycle ownership are all dichotomous variables describing whether an individual's gender is male (1) or female (0), receives reimbursement (1) or not (0), owns a private bicycle (1) or not (0). Household income levels are as follows <€12,500 (1), €12,500–26,200 (2), €26,200–38,800 (3), €38,800–65,000 (4), €65,000–77,500 (5), >=€77,500 (6). A 5-point scale from 1 to 5 was used for the built environment variables, with a highly urbanised area defined as a municipality > 2500 inhabitants/km2 (5) and a non-urbanised area defined as a municipality < 500 inhabitants/km2 (1).

3.3. Sample description

Table 2 shows the means and standard deviations of the time-varying variables, which are stable over four years. The average preference towards cycling ranges from 0.18 to 0.22, with a slight increase in 2014. The perceived bikeability is high, above 4.00 in each year, and stabilises at an average of 4.08. The distance travelled by bicycle varies between 8.36 and 9.24 km. Table 3 shows the descriptive statistics of the explanatory variables, where the data are calculated using the average of the four waves. The composition

Table 1
Mean statistics for key variables between total sample and sample participated in all four waves.

	Cycling preference	Perceived bikeability	Cycling distance
Total sample	0.200	4.078	8.798
Sample participated in all four waves	0.198	4.038	8.937

Table 2
Sample characteristics of preference, perceived bikeability and travel behaviour from wave 1 through 4 (2013–2016) (n = 1,203).

		2013	2014	2015	2016
Preference	Mean	0.202	0.215	0.197	0.189
	SD	0.006	0.007	0.006	0.006
Perceived bikeability	Mean	4.086	4.069	4.106	4.053
	SD	0.022	0.020	0.020	0.021
Travel behaviour	Mean	8.363	9.239	8.611	8.978
(cycling distance/km)	SD	0.457	0.621	0.541	0.783

of the sample is quite representative of the Dutch population. It can be seen that just over one in eight respondents (12.5 %) received the bicycle allowance, while 79.1 % owned a conventional bicycle.

4. Methodology

To analyse the longitudinal associations between perceived bikeability, cycling preferences, and cycling distance, the Cross-Lagged Panel Model (CLPM) and the Random Intercept Cross-Lagged Panel Model (RI-CLPM) can be used, both of which are Structural Equation Models (SEM) that allow for the examination of causal relationships between variables measured at two or more points in time. The CLPM specifies auto-regressive relationships, which are supposed to control for the stability of a variable over time. The cross-lagged relationships between the variables are then supposed to represent the causal processes.

However, autoregressive parameters are not able to correctly control for the trait-like, time-invariant nature in CLPM. As a result, the RI-CLPM decomposes the observed variables into two parts, including stable between-person differences that represents the individual's trait-like deviation from the means and within-person dynamics which measures temporal deviations from their expected scores (Mulder and Hamaker, 2021).

4.1. Cross-Lagged Panel model (CLPM)

Fig. 1 shows the CLPM framework, which aims to assess the direction of influence between perceived bikeability, cycling preferences and cycling distance using panel data. We estimated: (a) stability paths (e.g., autoregressive path from preferences at $t1$ to $t2$); (b) cross-lagged paths (e.g., prospective path from cycling preferences at $t1$ to cycling distance at $t2$); (c) correlations at $t1$ for the initial overlap; and (d) correlated changes over $t2$ to $t4$ between all study variables (dotted line in Fig. 1). In addition, the model also included gender, household income, reimbursement, bicycle ownership and built environment as covariates. Measurement equations for CLPM can be expressed as:

$$x_{it} = \sigma_t + p_{it} \tag{1}$$

$$y_{it} = \epsilon_t + q_{it} \tag{2}$$

Table 3
Sample characteristics of explanatory variables (n = 1,203).

Variable	Description	Ratio
Gender	Male	45.6 %
	Female	54.4 %
Household income	more than 2x the national benchmark income (>=77,500)	10.4 %
(€/year)	2x the national benchmark income (65,000–77,500)	7.5 %
	1-2x the national benchmark income (38,800–65,000)	28.1 %
	national benchmark income (26,200–38,800)	23.3 %
	below the national benchmark income (12,500–26,200)	15.7 %
	minimum (<12,500)	15.0 %
Reimbursement		12.5 %
Bicycle ownership		79.1 %
Built environment (inhabitants/km^2)	Very highly urbanized (>2500)	18.3 %
	Highly urbanized (1500——2500)	29.5 %
	Moderately urbanized (1000——1500)	24.0 %
	Low urbanization (500——1000)	19.5 %
	Non-urbanized area (<500)	8.7 %

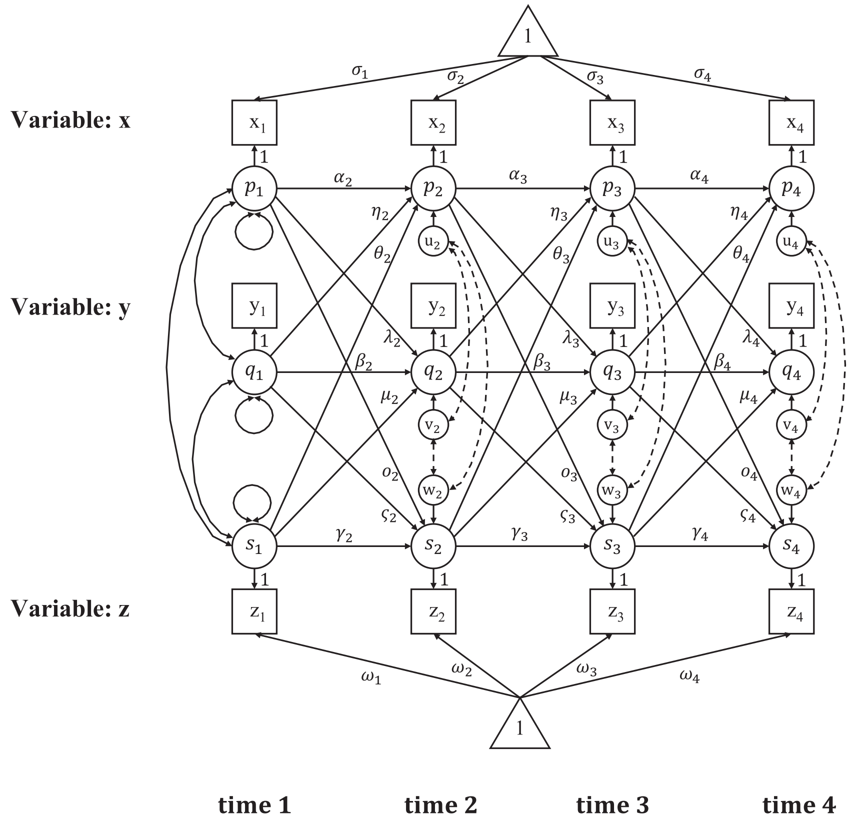

Fig. 1. CLPM model for four waves of data. Triangles represent constants (for the mean structure); squares denote observed variables; circles represent"latent" variables. Note that paths from constants of y are not displayed for the sake of clarity.

$$z_{it} = \omega_t + s_{it} \tag{3}$$

with

$$p_{it} = \alpha_t p_{i,t-1} + \eta_t q_{i,t-1} + \theta_t s_{i,t-1} + u_{it} \tag{4}$$

$$q_{it} = \beta_t q_{i,t-1} + \lambda_t p_{i,t-1} + \mu_t s_{i,t-1} + v_{it} \tag{5}$$

$$s_{it} = \gamma_t s_{i,t-1} + o_t p_{i,t-1} + \varsigma_t q_{i,t-1} + w_{it} \tag{6}$$

where.

x_{it} = cycling preferences of individual i at time t.
y_{it} = cycling distance of individual i at time t.
z_{it} = perceived bikeability of individual i at time t.
σ_t, $\in_t$ and ω_t are the grand means at time t for cycling preferences, cycling distance and perceived bikeability.
p_{it}, q_{it} and s_{it} are the individual temporal deviation terms from the time varying group means.
α_t, β_t and γ_t are the autoregressive parameters.
η_t, θ_t, λ_t, μ_t,o_t and ς_t are the cross-lagged parameters.
u_{it}, v_{it} and w_{it} are the between individual time-varying error terms.

4.2. Random Intercept Cross-Lagged Panel model (RI-CLPM)

Fig. 2 shows the RI-CLPM framework. For the within-person parts, we estimated: (a) stability paths, which represent the within-person carry-over effects for the same variable (e.g., autoregressive path from cycling preferences at $t1$ to $t2$); (b) cross-lagged paths, which capture the within-person effect of one variable at a previous time on another variable at the following time (e.g., prospective path from cycling preferences at $t1$ to cycling distance at $t2$); (c) correlations at $t1$ for the initial overlap; and (d) correlated changes over $t2$ to $t4$ among the within-person components of the study variables. (dotted line in Fig. 2). For the between-person parts, three random intercepts were added for cycling preferences (denoted by κ), cycling distance (denoted by φ), and perceived bikeability (denoted by τ) respectively, to capture how individuals differed from each other. Similar to the CLPM, the model also included gender,

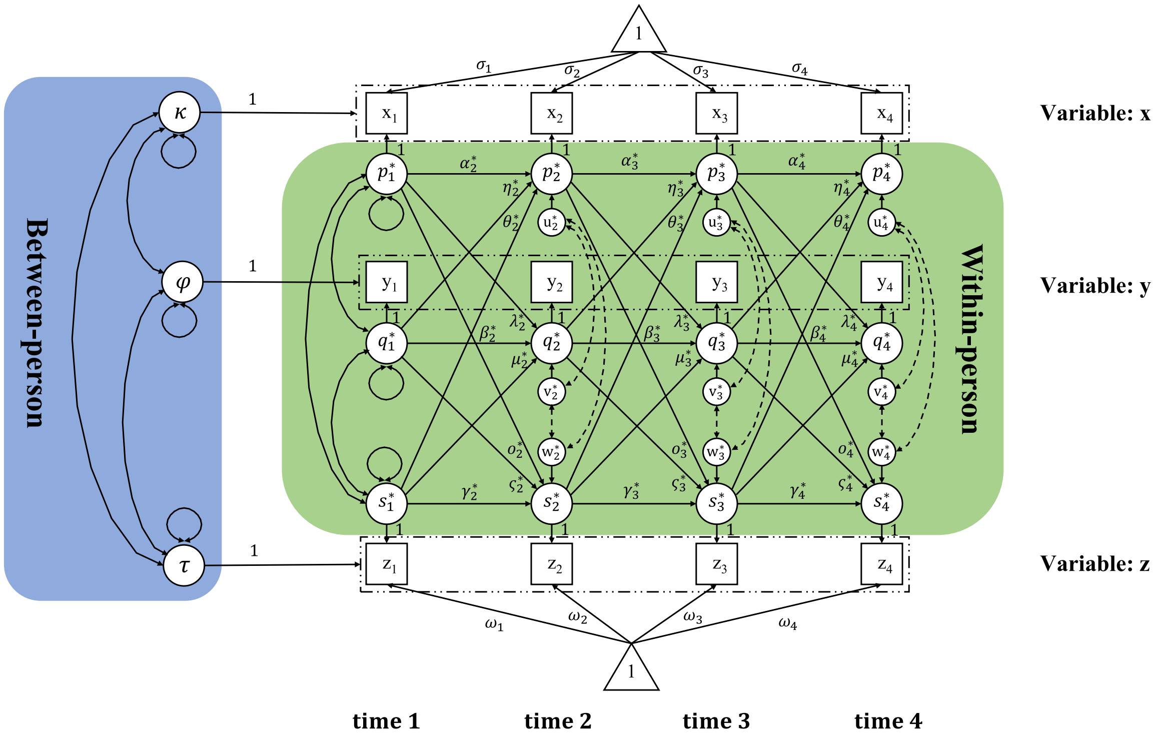

Fig. 2. RI-CLPM model for four waves of data. Triangles represent constants (for the mean structure); squares denote observed variables; circles represent"latent" variables. Note that paths from constants of y are not displayed for the sake of clarity.

household income, reimbursement, bicycle ownership and built environment as covariates. The measurement equations for the RI-CLPM can be expressed as:

$$x_{it} = \sigma_t + \kappa_i + p_{it}^{*} \tag{7}$$

$$y_{it} = \epsilon_t + \varphi_i + q_{it}^{*} \tag{8}$$

$$z_{it} = \omega_t + \tau_i + s_{it}^{*} \tag{9}$$

with

$$p_{it}^{*} = \alpha_t^{*} p_{i,t-1}^{*} + \eta_t^{*} q_{i,t-1}^{*} + \theta_t^{*} s_{i,t-1}^{*} + u_{it}^{*} \tag{10}$$

$$q_{it}^{*} = \beta_t^{*} q_{i,t-1}^{*} + \lambda_t^{*} p_{i,t-1}^{*} + \mu_t^{*} s_{i,t-1}^{*} + v_{it}^{*} \tag{11}$$

$$s_{it}^{*} = \gamma_t^{*} s_{i,t-1}^{*} + o_t^{*} p_{i,t-1}^{*} + \varsigma_t^{*} q_{i,t-1}^{*} + w_{it}^{*} \tag{12}$$

where.
x_{it} = cycling preferences of individual i at time t.
y_{it} = cycling distance of individual i at time t.
z_{it} = perceived bikeability of individual i at time t.
σ_t, ϵ_t and ω_t are the grand means at time t for cycling preferences, cycling distance and perceived bikeability.
κ_i, φ_i and τ_i are the individual's trait-like deviations from these means.
p_{it}^{*}, q_{it}^{*} and s_{it}^{*} are the individual's temporal deviations from their expected scores rather than from the group means.
α_t^{*}, β_t^{*} and γ_t^{*} are the autoregressive parameters.
η_t^{*}, θ_t^{*}, λ_t^{*}, μ_t^{*}, o_t^{*} and ς_t^{*} are the cross-lagged parameters.
u_{it}^{*}, v_{it}^{*} and w_{it}^{*} are the within individual time-varying error terms.

4.3. Model estimation

Both the CLPM and the RI-CLPM were fitted in the Mplus programme using maximum likelihood (ML) estimators. Three model fit indices are used for model evaluation, including comparative fit index (CFI), root mean square error of approximation (RMSEA) and standard root mean square residual (SRMR). The acceptable values of each fit index are CFI > 0.900, RMSEA < 0.080 and SRMR < 0.080 (Hihara et al., 2021; Olde Kalter et al., 2021). The following parameters are constrained to be equal across waves to improve estimation precision and ease of interpretation, including autoregressive, cross-lagged parameters and within-wave correlations. In addition, the cycling distance variable was used in logarithmic form in the final model because original data were left-skewed and showed a normal distribution when logarithms were used.

5. Results

5.1. Overview of the model fits

Table 4 shows the model fits of the CLPM and RI-CLPM. The CLPM fits the data relatively poorly with unsatisfactory CFI (0.888), RMSEA (0.080), and SRMR (0.069) values. The RI-CLPM provides a much better fit to the data, as indicated by the CFI (0.991), RMSEA (0.021), and SRMR (0.025). All these values indicate a good model fit. As discussed in the Methodology, the autoregressive parameters in RI-CLPM represent the within-person carryover effect rather than the rank order stability of individuals in CLPM. This results in a relatively large increase in model fit.

5.2. Cross-lagged panel models

The autoregressive effects for cycling preferences(α_t), distance(β_t) and perceived bikeability (γ_t) are all positive and significant (see Fig. 3 and Table 5). For each respondent, the value of their perceived bikeability, cycling preferences and distance tended to remain the same from time t-1 to time t. The most stable autoregressive effects are cycling preferences ($\alpha_t = 0.596$, 0.628, and 0.613), followed by perceived bikeability ($\gamma_t = 0.427$, 0.421, and 0.407) and distance ($\beta_t = 0.374$, 0.378, and 0.391).

In terms of the cross-lagged effects, the results show that the cross-lagged effects (η_t, θ_t, λ_t, μ_t,o_t and ς_t) between cycling preferences, distance and perceived bikeability are not significant for all relationships. Cycling preferences shows a significant and positive regression on both the later measures of distance ($\lambda_t = 0.227$, 0.233, and 0.236) and perceived bikeability ($o_t = 0.034$, 0.036, and 0.036), indicating that if a respondent has a stronger cycling preference at time t-1, the perceived bikeability and cycling distance at time t are likely to increase. Cycling distance only has a significant effect on later preferences ($\eta_t = 0.143$, 0.148, and 0.148), whereas perceived bikeability only significantly affects later cycling distance ($\mu_t = 0.043$, 0.041, and 0.041). However, there are no significant cross-lagged effects of cycling distance on perceived bikeability and perceived bikeability on preferences across the waves.

Regarding the correlations, the correlation between cycling preferences and distance is significant ($u_{it}{*}v_{it} = 0.462$, 0.171, 0.175, and 0.151, all $p < 0.01$). This means that people who reported stronger preferences towards cycling over time are more likely to cycle longer distances over time than other people. The initial overlap is fairly strong compared to the other waves ($u_{it}{*}v_{it} = 0.462$). The lower and significant correlations from wave 2 to wave 4 indicate that the simultaneous changes in preferences and distance could be explained, and that both variables have changed in similar directions due to influences not included in the model. No significant correlation is found between the other two pairs.

Table 6 shows the standardised effects of the five exogenous variables, including gender, household income, reimbursement for cycling, bicycle ownership and built environment. Men have lower cycling preferences but higher perceived bikeability than women. Cycling longer distances is less common among individuals with higher income, whereas they perceive higher bikeability. People who received reimbursement and owned a private bicycle are more likely to have stronger cycling preferences and to cycle longer distances. A positive association is found between living in urban areas and cycling preferences.

5.3. Random intercept cross-lagged panel model

The estimated parameters for the autoregressive effects represent within-person dynamics, where the effects for cycling preferences (α_t^*) and distance (β_t^*) are both positive and significant (see Fig. 4 and Table 7). Positive estimates reflect that if an individual had a higher cycling preference or distance at time t-1, then this individual is likely to have a higher cycling preference or distance at time t as well. No significant autoregressive effects are found for perceived bikeability, indicating that an individual's perceived bikeability at time t-1 does not affect their perceived bikeability in the next year. The autoregressive effects are the largest in the model compared to cross-lagged effect and within-person correlations, suggesting that the cycling preferences and distance at time t-1 are the main predictors of each of these factors separately at time t. In addition, the autoregressive effects are stronger for cycling preferences ($\alpha_t^* = 0.172$, 0.171, and 0.170) compared to the distance ($\beta_t^* = 0.128$, 0.134, and 0.134).

Table 4
Model Fits for CLPM and RI-CLPM.

Models	Model fits		
	CFI	RMSEA	SRMR
CLPM	0.888	0.080	0.069
RI-CLPM	0.991	0.021	0.025

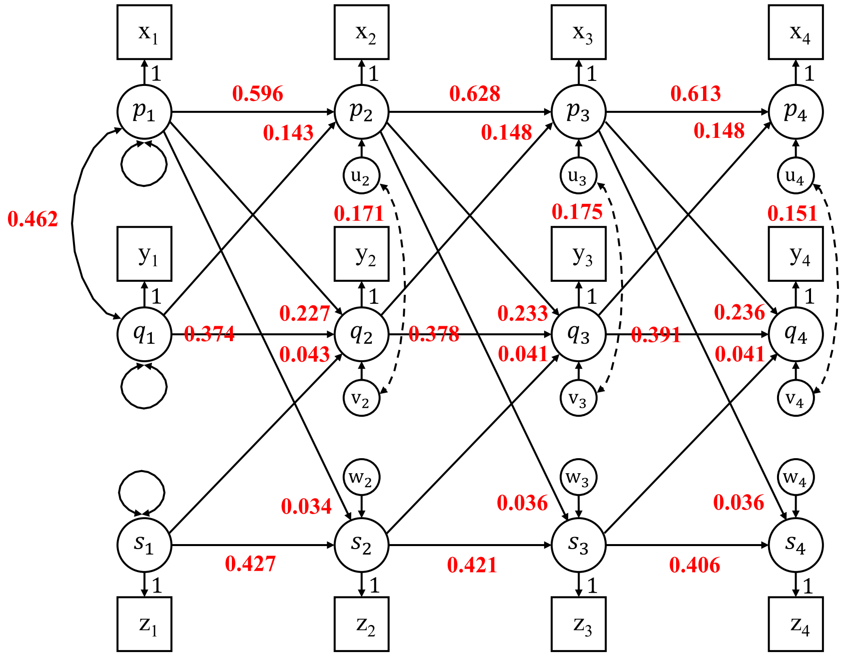

Fig. 3. Significant standardised effects of CLPM.

Table 5
Autoregressive and cross-lagged effects between perceived bikeability, cycling preference and behaviour (n = 1,203).

Year	2013	2014	2015	2016
	Std. Coef.	Std. Coef.	Std. Coef.	Std. Coef.
Autoregressive effects				
Preference.t-1 => Preference.t (α_t)		**0.596****	**0.628****	**0.613****
Distance.t-1 => Distance.t (β_t)		**0.374****	**0.378****	**0.391****
PB.t-1 => PB.t (γ_t)		**0.427****	**0.421****	**0.406****
Cross-lagged effects				
Distance.t-1 => Preference.t (η_t)		**0.143****	**0.148****	**0.148****
PB.t-1 => Preference.t (θ_t)		0.013	0.012	0.012
Preference.t-1=> Distance.t (λ_t)		**0.227****	**0.233****	**0.236****
PB.t-1=> Distance.t (μ_t)		**0.043****	**0.041****	**0.041****
Preference.t-1=> PB.t (o_t)		**0.034***	**0.036***	**0.036***
Distance.t-1 => PB.t (ς_t)		0.024	0.025	0.025
Correlation				
Preference.t * Distance.t (u_{it}*v_{it})	**0.462****	**0.171****	**0.175****	**0.151****
Preference.t * PB.t (u_{it}*w_{it})	0.012	0.041	0.026	0.024
Distance.t * PB.t (v_{it}*w_{it})	0.044	0.007	0.016	0.003

Note: **p < 0.01, **p < 0.05.

Table 6
Standardised effects of exogenous variables (n = 1,203).

	Preference	Cycling distance	Perceived bikeability
	Std. Coef.	Std. Coef.	Std. Coef.
Gender	**−0.055****	0.011	**0.038****
Income	−0.015	**−0.029***	**0.030***
Reimbursement	**0.074****	**0.105****	−0.007
Bicycle ownership	**0.055****	**0.043****	−0.007
Built environment	**0.053****	0.006	−0.015

Note: **p < 0.01, **p < 0.05.

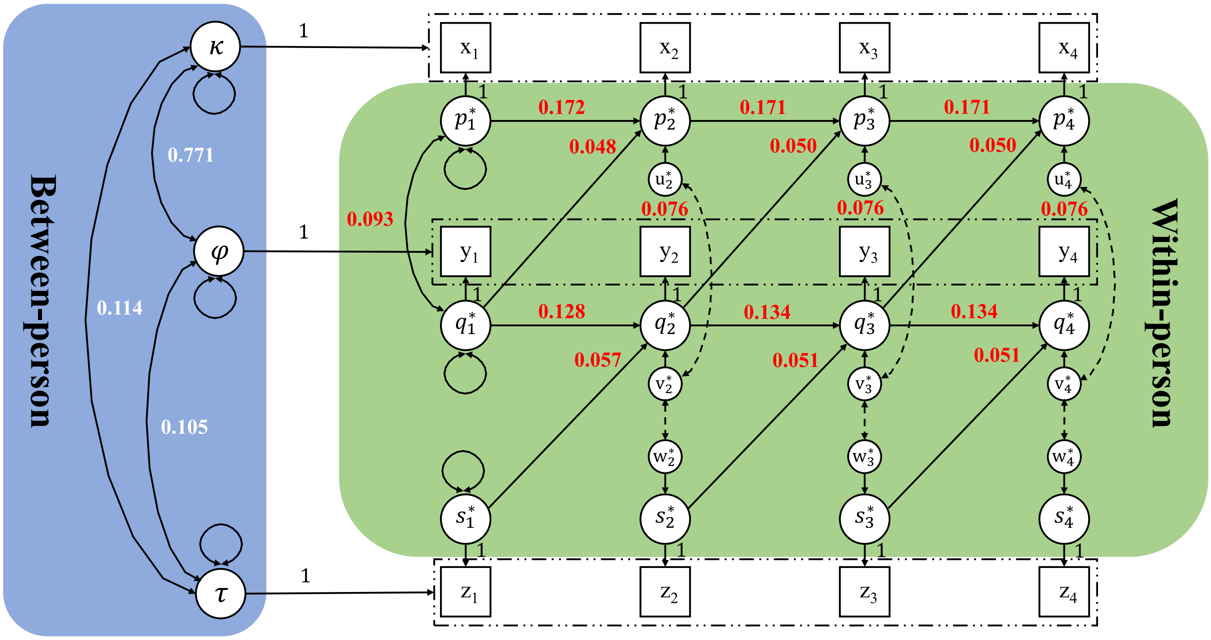

Fig. 4. Significant standardised effects of the RI-CLPM.

Table 7
Autoregressive and cross-lagged effects between perceived bikeability, cycling preference and behaviour (n = 1,203).

Year	2013	2014	2015	2016
	Std. Coef.	Std. Coef.	Std. Coef.	Std. Coef.
Autoregressive effects				
Preference.t-1 => Preference.t (α_t^*)		**0.172****	**0.171****	**0.170****
Distance.t-1 => Distance.t (β_t^*)		**0.128****	**0.134****	**0.134****
PB.t-1 => PB.t (γ_t^*)		0.020	0.018	0.018
Cross-lagged effects				
Distance.t-1 => Preference.t (η_t^*)		**0.048***	**0.050***	**0.050***
PB.t-1 => Preference.t (θ_t^*)		−0.011	−0.010	−0.010
Preference.t-1=> Distance.t (λ_t^*)		0.033	0.033	0.033
PB.t-1=> Distance.t (μ_t^*)		**0.057***	**0.051***	**0.051***
Preference.t-1=> PB.t (o_t^*)		0.010	0.010	0.010
Distance.t-1 => PB.t (ς_t^*)		0.034	0.036	0.036
Correlation within person				
Preference.t * Distance.t ($u_{it}^* {*} v_{it}^*$)	**0.093***	**0.076****	**0.076****	**0.076****
Preference.t * PB.t ($u_{it}^* {*} w_{it}^*$)	−0.054	0.028	0.028	0.028
Distance.t * PB.t ($v_{it}^* {*} w_{it}^*$)	−0.006	0.038	0.038	0.038
Correlation between person				
Preference * Distance ($\kappa{*}\varphi$)	**0.771****			
Preference * PB ($\kappa{*}\tau$)	**0.114****			
Distance * PB ($\varphi{*}\tau$)	**0.105***			

Note: **p < 0.01, **p < 0.05.

For the cross-lagged parameters (η_t^*, θ_t^*, λ_t^*, μ_t^*, o_t^* and ς_t^*), only cycling distance shows a significant effect on later cycling preferences ($\eta_t^* = 0.048$, 0.050, and 0.050), and perceived bikeability significantly affects later cycling distance ($\mu_t^* = 0.057$, 0.051, and 0.051) (Table 7). The standardised estimated parameter for the effect of cycling distance in 2013 on cycling preferences in 2014 is 0.048, suggesting that if an individual's cycling distance was higher at time t-1, the higher cycling distance will increase their cycling preferences at time t. Additionally, respondents with higher perceived bikeability at time t-1 will tend to cycle longer distance at time t. However, there are no significant effects for the other cross-lagged effects between cycling preferences, distance, and perceived bikeability across the waves. For example, the insignificance of the cross-lagged effects of cycling distance on perceived bikeability means that an increase in cycling distance does not necessarily lead to an increase in perceived bikeability in the following year.

The between-person correlation shows the relationship between cycling preferences, distance and perceived bikeability for different people, while the within-person correlation makes the causal inference between cycling preferences, distance and perceived bikeability for the same person at different times. There is a significant correlation between cycling preference, cycling distance and perceived bikeability between people (Table 7). The between-person correlation between cycling preferences and distance is very high ($\kappa^*\varphi = 0.771$), meaning that people who reported stronger preferences towards cycling over time are more likely to have cycled more distance over time than other people. Also, people who had a stronger preference for the bicycle or who cycled more distance tend to have higher perceived bikeability over time than other users ($\kappa^*\tau = 0.114$, $\varphi^*\tau = 0.105$). Regarding the within-person correlation, only the correlation between cycling preferences and distance is significant ($u_{it}^{*} {}^{*} v_{it}^{*} = 0.093$, 0.076, 0.076, and 0.076) (Table 7). The positive intrapersonal correlations reflect that at the personal level, an above-average cycling preferences at time t is associated with an above-average cycling distance at time t, in addition to the between-person correlation. For the other two pairs, no significant within-person correlation is found. This means that the individual who had a higher perceived bikeability at time t does not necessarily have a stronger cycling preference or cycled more distances, or vice versa.

The significant effects of the five exogenous variables in RI-CLPM (Table 8) are mostly consistent with the results in CLPM (Table 6). The difference is that income now has a significant negative effect on cycling preferences, and the urban built environment significantly increases the cycling distance.

6. Discussion and implications

6.1. Discussion

The significant and positive the autoregressive effects indicated that the cycling preferences and cycling behaviour were stable over time for each individual (Table 7), which is consistent with our common sense. However, we didn't find the significant and positive the autoregressive effects of perceived bikeability (Table 7). This illustrates that perceived bikeability is more easily influenced. Men have higher perceived bikeability than women, and people with higher income perceive higher accessibility to cycling (Table 8). As the aim of this study is to examine the relationship between perceived bikeability, cycling preference and cycling distance rather than the factors that influence perceived bikeability, other potential influencing factors, such as the weather, travel intentions and traffic stress, are not fully considered in this research. Investigating the factors that influence perceived bikeability will be a future research direction for this study, so it will not be discussed further here.

We also found that the autoregressive effects were the largest in the model, which is consistent with research results on past behaviour as a good predictor of current behaviour (Thøgersen, 2006). In our study, the autoregressive effects of cycling preferences are much higher than those of cycling distance. In contrast, Olde Kalter et al. (2021) concluded that the autoregressive effects of cycling frequency are two times higher than those of cycling preference. This may be explained by the different measurement and research groups. The previous research was based on the cycling frequency, not cycling distance in this study. And the participants were young adults, who may have different characteristics of autoregressive effects. Kroesen et al. (2017) also found that cycling use tends to be more stable than the attitudes towards cycling. However, the study only used two waves of data and it might be difficult to measure the autoregressive effects in a relatively short period of time.

Regarding the cross-lagged effects between cycling preferences and distance, previous studies on travel behaviour have shown a strong relationship between mode preference and mode use (Buehler, 2011; Gao et al., 2019; Haustein and Møller, 2016; Maldonado-Hinarejos et al., 2014). This indicates that people who express a preference for cycling are more likely to cycle longer distance than those who don't. However, there is no evidence to suggest that an individual who exhibits a greater cycling preference in the subsequent year will also cycle a greater distance. Based on four waves of panel data, we can conclude the causal relationship between cycling distance and preferences. People who cycled longer distances were more likely to have stronger cycling preferences later on. However, an increase in cycling preferences does not lead to an increase in cycling distance (Table 7). This means that changes in cycling behaviour are more likely to precede changes in preferences, rather than vice versa. This is in line with the findings of Olde Kalter et al. (2021), who found similar effects using the same method of RI-CLPM and a three-wave panel data of MPN.

In terms of the cross-lagged effects between cycling distance and perceived bikeability, the results of this study highlight the importance of considering the impact of perceived bikeability on changes in cycling behaviour (Table 7). There appears to be a causal relationship between perceived bikeability and cycling distance. Individuals who have a better perception of cycling infrastructure, i.e., those who possess comprehensive knowledge of the cycling transport system, are more likely to increase their cycling distance in the following year. However, no significant effects were found in the opposite direction, suggesting that changes in perceived bikeability are more likely to precede changes in cycling behaviour rather than vice versa. These findings are consistent those of previous studies that employed a cross-sectional data analysis approach. Blitz (2021) found that perceived cycling infrastructure would encourage cycling, while Guo and He (2021) found that perceived accessibility of DBS increases the choice of DBS-metro integration.

In terms of the model comparison between CLPM and RI-CLPM, the RI-CLPM fitted the data better overall, with a higher CFI, lower RMSEA, and lower SRMR than the CLPM (Table 4). The chi-squared difference test also showed that the p-value was less than 0.001, meaning that its estimation is more appropriate for interpreting the data. After accounting for the individual's trait-like deviation from the means, the within-person changes were much clearer and could be isolated to measure the temporal deviations from their expected values (Tao, 2024). The significant results of autoregressive effects for cycling perceived bikeability from CLPM were no longer

Table 8
Standardised effects of exogenous variables (n = 1,203).

	Preference	Cycling distance	Perceived bikeability
	Std. Coef.	Std. Coef.	Std. Coef.
Gender	**−0.133****	−0.019	**0.085***
Income	**−0.058***	**−0.080***	**0.072***
Reimbursement	**0.245****	**0.302****	−0.003
Bicycle ownership	**0.191****	**0.176****	0.000
Built environment	**0.147****	**0.069***	−0.041

Note: **p < 0.01, **p < 0.05.

significant in RI-CLPM (see Table 5 and Table 7). This means that people with higher perceived bikeability at time t-1 would generally still have higher perceived bikeability at time t. However, variations within the individual had no effect in this direction: a higher perceived bikeability at time t-1 would not result in a higher perceived bikeability at time t. The research methods that were unable to separate within-person from between-person effects would overestimate the size of the complementary effect to varying degrees. The overestimation also occurred in the cross-lagged effects of cycling preferences on distance and perceived bikeability.

6.2. Policy implications

Overall, this study provides new insight into the relationship between perceived bikeability, preferences and travel behaviour. The in-depth analysis of within-person changes can provide policymakers with implications for planning an appropriate cycling environment. Two policy recommendations are identified as follows.

Firstly, policymakers should recognise that perceived bikeability plays an important role in future cycling behaviour, as the cross-lagged effect of perceived bikeability on cycling distance was found to be significant and positive in our study. This suggests that an increase in perceived bikeability will lead to a change in cycling behaviour in the next year. Additionally, women and people with lower incomes have lower perceived bikeability. Related interventions might contribute to promoting cycling, but only where the residents perceived such improvements. In order to increase travellers' cycling distance, it is recommended that behaviour change interventions focus on strategies to improve the perception of the cycling infrastructure. For those neighbourhoods that already had a good cycling infrastructure, the perceived bikeability may be improved by increasing social media promotion of community cycling facilities or encouraging residents to participate in some cycling related activities. For those neighbourhoods with inadequate cycling infrastructure, it is more important to improve the perceived bikeability by providing information or the opportunities for residents to experience the changes in cycling infrastructure, rather than merely improving the cycling infrastructure itself. Previous research based on cross-sectional data has highlighted that cycling behaviour can be influenced by enhancing cycling preferences, but this does not imply causality. For instance, we can't conclude from the correlation that a change in people's preferences lead to a change in their behaviour. It is important for policymakers to focus on causality rather than misinterpretation the correlation between cycling preference and distance. The positive effects of perceived bikeability have been neglected in urban planning processes.

What's more, achieving structural changes in cycling behaviour requires timing and duration for the implementations of interventions. In our study, we found that perceived bikeability directly encourages individual cycling distances in the following year, with a lagged effect. An intervention which is designed to improve people's perceived bikeability may not result in people cycling more in the year after. Evaluations should take time into account when assessing the impact of policies, which means that a long-term evaluation of interventions should be more effective.

6.3. Research limitations and future research

The present study has two major limitations. Firstly, the measurement of cycling preference and perceived bikeability may oversimplify a complex construct. A psychometric scale encompassing a range of cognitive, affective, and behavioural dimensions, would have been more appropriate for the measurement of cycling preference. Employing a more comprehensive scale could better capture the multifaceted nature of perceived bikeability, which includes dimensions such as comfort, directness, coherence, attractiveness, and safety. Hence, future studies should ideally use measurements of cycling preference and perceived bikeability incorporating multiple Likert scales, increasing their validity and reliability. The second limitation relates to the fact that this study cannot identify the main factors explaining perceived bikeability, as the relevant variables, such as the weather, travel intentions, built environment and cycling infrastructure, were not available. The inclusion of these additional variables could have strengthened the model and facilitated the translation of the results into interventions.

There are at least two more interesting sources to explore for future work. On the one hand, a deeper understanding of the factors that influence perceived bikeability is needed. For example, examining the effects of changes in the built environment could provide valuable insights into how due to interventions affect perceived bikeability. On the other hand, this study used cycling distance to explore the relationship between cycling preferences, behaviour, and perceived bikeability. It would also be interesting to use the same research methods and panel data to measure cycling behaviour in terms of cycling duration, number of cycling trips or frequency of cycling.

7. Conclusion

This study used two methods including CLPM and RI-CLPM to analyse the causal relationship between cycling perceived bikeability, cycling preferences and cycling distance. In terms of within-person effects, the results showed that cycling preferences and distance had the positive autoregressive effects, with the largest estimate in the parts of the within-person effects. In addition, the perceived bikeability only had a significant cross-lagged effect on subsequent cycling distance, with no autoregressive effects. The positive parameter indicates that the observed increase in cycling distance during the second year can be attributed to improved perceived bikeability in the previous year. Further cross-lagged effects of cycling distance on subsequent preferences were found. Moreover, at the individual level, the intrapersonal correlations reflect a positive relationship between cycling preferences and distance. In terms of between-person effects, we found that perceived bikeability, cycling preferences and distance were all positively correlated with each other in both directions, where the correlation between cycling preferences and distance was the highest. The RI-CLPM showed a better model fit than the CLPM in interpreting the between- and within-person effects.

The empirical findings of this study have important implications for future research into the planning of the cycling infrastructure and the provision of more convenient and efficient services to improve the perceived bikeability. The validity of RI-CLPM for the analysis of longitudinal data is demonstrated to provide model support for other related future studies.

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CRediT authorship contribution statement

Cong Qi: Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jonas De Vos:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **Xiucheng Guo:** Writing – review & editing, Formal analysis.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The authors do not have permission to share data.

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