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Understanding the Relation of Psychological/Behavioral Factors and Cycling During the Covid-19 Pandemic: A Case Study in Iran

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Abstract
Previous research on travel behavior has concentrated on the behavior of traveling by cars, especially by private vehicles, while the research on cycling has focused on cycling infrastructure, the built environment, and the natural environment. Furthermore, the studies conducted during pandemics are mostly based on behavioral changes in motorized transportation. The present research tries to identify and evaluate the variables influencing cyclist behavior during covid-19 pandemic. In this research, the sample size retrieved from a survey of 375 participants was checked with Cronbach's alpha standard and estimated using confirmatory factor analysis. Results show that the variables related to health protocols can greatly impact knowing the behavior of cyclists in the time of Covid-19. Furthermore, the results show that the health issues of shared bikes can be an obstacle for people to use them more.

Keywords Transportation planning · Cycling behavior · Confirmatory Factor Analysis (CFA) · Subjective factors · Structural equation modeling

1 Introduction

One of the most important issues affecting the transportation industry is the impact of infectious diseases on people's use of various modes of transportation[1, 2]. Each country, according to its economic, social and cultural conditions, imposes certain restrictions, such as travel restrictions, to control the spread of pollution[3, 4].

One of the most important measures to control infectious diseases is closing schools and holding classes online. In addition to reducing communication between people, especially school service drivers and teenagers, this measure also helps to reduce the number of covid-19 outbreaks and reduce air pollution and fuel consumption. It should not be forgotten that traveling is one of the most important factors in the spread of Covid-19.

About three years have passed since the first report of Covid-19 disease and countries are still trying to take measures to improve their economic activities. On the other hand, they are trying to solve the environmental problems that they were struggling with before the start of Covid-19. The spread of the covid-19 virus has caused urban transportation planning to be more complex than before.

Several recent studies have highlighted the changes in active transport behavior [5, 6], as well as bike-sharing during the pandemic [7].

As a result of social distancing rules, most people in Tehran use their cars on most trips, which contributes to issues, such as air pollution. Consequently, from December 1 to January 14, 2020, the residents of the city endured 26 days of high air pollution deemed dangerous to sensitive groups. Despite the widespread usage of private cars, the public transport system is still crowded in terms of the large population of the city (around 8 million people). Therefore, policymakers and transportation planners should be presented with an in-depth analysis of cycling behavior to make informed decisions intended to promote the utility of using bicycles.

In recent decades, numerous studies tried to promote the utility of cycling. In particular, many researchers have explored the possibility of increasing the use of active transport. For this purpose, multiple variables were identified and various categories have been developed [8, 9], including individual characteristics, household characteristics, trip characteristics, built environment, season, weather

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characteristics, and work conditions. The majority of previous studies have divided the variables which affect using active transport into objective and subjective categories [10]. In recent decades, although studies on latent variables have increasingly obtained more accurate findings, not all of the previous research has reported consistent results in terms of the differences in the data sources and methodologies used to study latent variables. While the researchers have explored non-motorized transportation, the latent variables affecting cycling during the covid-19 pandemic still need to be investigated.

This research aims to contribute to the literature by (1) identifying hidden variables affecting cyclist behavior during covid-19 pandemic (e.g. Hygiene shared-bike); (2) identifying three variables based on several questions, the confirmatory factor analysis of the relationship between each question and the latent variable; (3) examining the effects of individual subjective factors as well as *environmental characteristics*, *health protocols,* and *self-health protocols* and the effect of socio-economic characteristics; (4) providing an insight into cycling in Iran as a developing country, which has not been thoroughly addressed by previous research.

Confirmatory factor analysis (CFA) was used to develop a cycling behavior model utilizing unobserved latent factors that underlie the observed variables. The final model indicates that health protocols have a strong negative effect on cycling behavior (the stricter the health protocols, the less inclined individuals are to ride a bike).

In this study, we tried to measure the influence rate of covid-19 pandemic restrictions and individual's actions on cycling behavior. From this point of view, chapter 2 reviews the literature on cycling behavior and the factors affecting cycling. Chapter 3 provides a description of the data as well as a comparison of the data to the information derived from the master plan of the city and the methodology used in this paper. Chapter 4 presents the confirmatory factor analysis. The final chapter presents the conclusions of the research, a summary of the main findings, and recommendations for policymakers and transportation professionals.

2 Literature Review

Earlier studies reveal that the cycling behavior of regular riders (private bicycle riders) tends to be influenced by environmental factors, including population density, land use mix, green space, cycling facilities, and safety [11]. Besides, Tehran transport master plan in 2008 was nearly the first governmental study with a section on active transportation. After that, some studies were held on active transport and sustainability. The most recent study of the Tehran municipality is about green transportation with a good vision of active transport. The outcome of that study indicates that traffic calming is the key to increase the rate of cycling. This study continues that the municipality should take steps to create infrastructure for using e-bikes and e-scooters as soon as possible.

However, no previous study tried to determine how cycling behavior changes during pandemics and, in particular, how it is influenced by the imposed health protocols and restrictions such as lockdowns. This study aims to answer such questions. In the following, some of the important issues reported by the literature are reviewed.

2.1 Individual Characteristics

Age and gender are some of the variables most commonly associated with bicycling. Studies on the effects of age on traveling by bicycle have reached different conclusions. While some researchers have reported that being young (ages 18–24) has a negative effect on bicycling [12], the majority of studies have concluded that being young raises the likelihood of bicycling [13–16]. Another study reports that the likelihood of bicycling increases among young people (ages 12–18), while they are having more snack occasions per week, and it is more among females [17]. Bicycling rates are affected by gender. Many studies have reported that boys are more likely than girls to cycle[15, 18–27]. However, some studies have not confirmed this finding [12, 17]. Some researchers have concluded that the majority of those who cycle to work are male[28, 29]. For instance, Emond and Handy found that male students are much more likely than female students to use a bicycle[30]. Another factor that reduces the likelihood of cycling is obesity [31], those who used motor vehicles were significantly more obese and overweight than participants who walked or biked to school[32]. Moreover, adopting appropriate policies can promote using the bicycles among overweight individuals, thereby reducing the negative impact of the covid-19virus pandemic. Another study from a city in Iran reveals that it does not matter what kind of facilities were created for cycling in the city, individuals don't like biking at all and prefer to use their own car[33].

2.2 Trip Characteristics

Many studies have indicated that travel time has a negative effect on the likelihood of cycling [34–38]. In a study that was conducted on students in Tehran showed that every minute of travel time increase, discourages using the active modes[39].

Zahran et al. ranked the top 25 countries by the percentage of workers who commute to work by bicycle as their primary means of transportation. The results of the study showed that for every additional minute of average journey time, the expected number of bike commuters decreases by

5.8% [40]. Another study found that reductions in travel time resulting from the provision of route facilities promote cycling [41]. Another important factor in the probability of choosing active transport is trip distance. According to the majority of previous studies, higher travel distances result in a lower likelihood of bicycling [8, 19, 21, 28, 34, 35, 42, 43]. Another study found that short distances promote the use of bicycles and reduce the total of vehicle kilometers in Belgium [44]. Some other studies acclaimed that the recreational and social purpose of bicycling greatly affect the likelihood of bicycling [19, 45], which was rejected by several other studies [12].

2.3 Population Density

Rietveld and Daniel report that using the bicycles is less common in low-population density areas where there might be fewer opportunities to make short trips [46] while another study concludes that an increase in population density promotes the likelihood of cycling in commuters [28].

Moreover, the results reported by several studies indicate that high population density has a positive influence on the likelihood of cycling [42, 47–49]. Furthermore, the women prefer to use spaces that are more stimulating and in which other individuals are present that is very important in Iran which can induce a sense of being safe to them[27].

Home location is another significant built environment factor. According to Plaut, people that live in rural regions are less likely to use a bicycle on their trips [29], while another study indicates that people who live in towns or the suburbs use a bicycle more often than those living in urban centers [50]. Moreover, the traffic flow variable (noise, emissions) can have an important effect on the likelihood of bicycling [40, 44], but the variable still needs to be investigated more thoroughly. According to Rietveld and Daniel, physical effort is a significant factor (slopes, frequent stops) [46], and other studies have highlighted the disadvantages of hilliness/slopes on the likelihood of bicycling [14, 51]. However, the extent of the effect depends on the amount of slop\hilliness and the physical strength of each individual.

2.4 Natural Environment Characteristics

Type your Rainfall and low temperatures have a relatively high negative impact on the tendency to use bicycles on commutes [28]. Another study indicates that rainy weather has a large negative impact on cycling compared to windy weather [41]. Dell'olio et al. report that only 0.3% of urban journeys are made in a medium-sized city like Santander, Spain, in terms of abundant rainfall [52]. They suggest that low temperatures have a negative effect on cycling. Another study reveals that using canopies in the walking/cycling pathways can increase the rate of active transport on sunny days[53].

2.5 Work Conditions

Some researchers have identified employment status as a major factor influencing the likelihood of using a bicycle, with students and the unemployed being more likely to ride a bicycle on their trips [54–56]. Another variable is hours of work, with longer work hours discouraging the use of bicycles [57, 58].

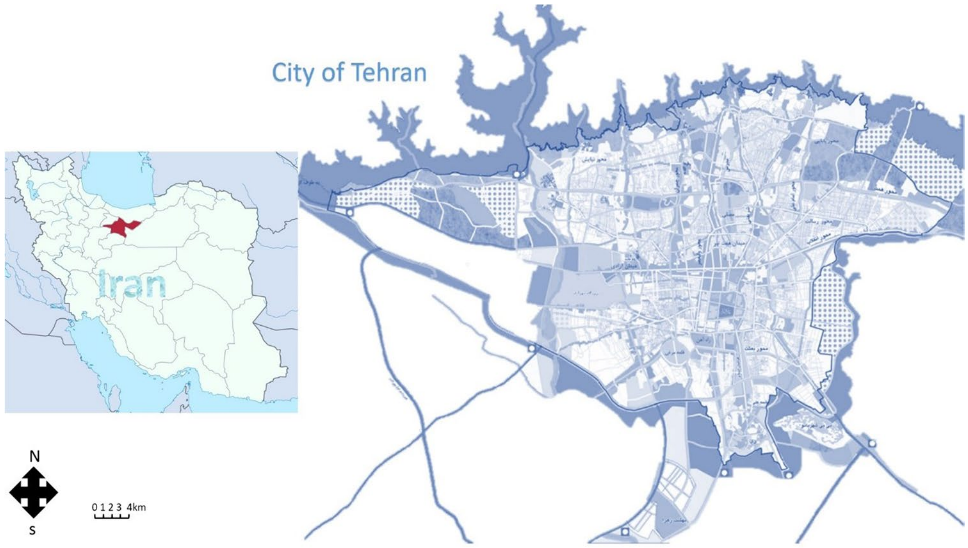
In general, although the variables discussed above are objective, there are subjective variables that influence the promotion of active transport. That is why latent variables and their indicators should be considered. Latent variables cannot be directly measured and require indicators to be estimated. Many studies have investigated the subjective and objective variables that might affect active transport, especially in the last decade. Taylor and Mahmassani introduced bicycle security and cost importance as new latent variables influencing the utility of bicycle use [25]. Moreover, additional variables were proposed, such as the positive influence of convenience [59, 60], social norms [50] and cycling ability [15, 61]. Sigurdardottir et al. explored the positive effect of being anti-car, the positive experience of riding futuristic bicycles and identified some new variables in the field of active transport [62]. One of the best ways to simultaneously model explanatory and latent variables is using structural equation modeling (SEM) in line with confirmatory factor analysis, which assigns coefficients to path relationships, and thus provides a more precise indication of the interrelationships among the variables. Although SEM studies are significant in the social and psychological sciences, they have not been extensively developed to model the bicycle mode choice problem [10]. Sigurdardottir et al. first studied the choice of bicycles using SEM models [62]. Their research addresses the gap by investigating the latent variables and objective factors influencing cycling behavior during pandemics. The model presented in the following section can be developed for normal situations as well.

Appendix Table 5, represent all of previous studies reviewed in this article (Fig. 1).

3 Data and Methodology

This section introduces sampling, data collection, and objective and subjective variables, which are employed in the model and modeling process using confirmatory factor analysis (CFA).

Fig. 1 The location and development pattern of Tehran



3.1 Case Study and the Survey

This study was conducted in Tehran, which is the most populous city in the country. According to 2015 census data, more than 6.900.000 individuals over the age of 18, which is the age group of the case study, live in the city. On the other hand, since the onset of the covid-19virus pandemic, more than 1.300.000 people were infected, more than 56.000 of whom have died. There are no official statistics on the total prevalence of covid-19virus in Tehran, but the death toll reportedly dropped during February—March 2021.

On the other hand, the majority of the population is eager to use private cars in terms of the convenience as well as the lack of a decent public transport system. The number of trips made by private cars is 8 times the capacity of the streets, which contributes to air pollution. Moreover, the city has the busiest public transportation system in the country, which exacerbates the pandemic. Tehran's location on the foothills of the Alborz mountain range and the existence of a steep slope in the northern regions of the city could also discourage the use of bicycles, which can be explored by future research.

For the purposes of this study, a survey covering individual characteristics such as age, gender, marital status, and level of education was conducted.

Regarding the limitations caused by the spread of the covid-19virus, the questionnaire was conducted online, the announcement of responses to this online questionnaire was made through direct phone call, text messages, virtual space and channels and groups. Furthermore, to increase participation, a cash reward was also given to the respondents as part of a lottery. Information were collected from 336 participants during two weeks based on Cochran's formula [63]. The collected data is compared to data from the 2015 census, which can be seen in Table 1. The number of male respondents is higher than the official statistics since men constitute the majority of commuters and have more Internet access. On the other hand, the high percentage of single participants is in terms of the fact that people with higher

Table 1 Demographics: gender, marital status, age, education, and car ownership (s)($n=375$)

		Number	Percent(%)	Percent(%) in 2015
Gender	Male	210	56	49.76
	Female	165	44	50.24
Marital status	Single	158	42	5
	Married	217	58	95
Age	18–29	6	2	24
	30–39	122	33	27
	40–49	157	42	18
	50–60	66	18	16
	> 60	24	5	15
Education	Diploma	30	8	NA
	Bachelor	170	45	NA
	Master	127	34	NA
	PhD	48	13	NA
Car ownership	Have car	254	68	NA
	Do not have	121	32	NA

NA Not available

education tend to be singles with more access to the Internet. In other words, marriages are more common among those with lower education (who have less access to the Internet). On the other hand, as people get older, their ability to use the Internet and respond to online surveys decreases, which is another reason for the lower number of older people compared to the data collected in 2015. Moreover, the relative absence of respondents aged 18—29 may be in terms of a lack of public participation by this age group.

The participants were reminded that all questions should be answered considering the covid-19 virus pandemic. The analysis section is based on both revealed and stated preference data simultaneously collected by the survey. At the beginning of the advertisement for answering the online questionnaire, we might face low participation from individuals. Only those respondents who stated they would be willing to use the bicycle as a mode of transport on any of the trips could answer the survey. However, with the acceptance of the people, it was tried that every person who participates in this action (regardless of being a cyclist or not) is willing to answer the questionnaire.

3.2 Analysis

To understand cycling behavior during covid-19, it is necessary to examine several unobserved variables. The main latent variable is cyclist behavior, which was defined via three other latent variables, namely environmental characteristics, health protocols, and self-health measures. There are three main latent variables, which are described by indicators. A total of 14 indicators were used to define latent variables that could indicate the effect of the pandemic on cycling behavior (i.e. the effect of coldness on the spread of covid-19). Three variables were used to define environmental characteristics (namely coldness, density, and slope) five variables to define health protocols, and six variables to define self-health protocols. All of these variables are estimated using confirmatory factor analysis (CFA) [64]. Table 2 shows the abbreviation and definition of each variable. Structural equation modeling is the second generation of statistical analysis techniques used to analyze the interrelationships among multiple model variables. Interrelationships among variables can be represented by a set of simple or multiple regression equations. Confirmatory factor analysis (CFA) uses a combination of quantitative data and causal or correlational assumptions in modeling.

CFA is a statistical technique for solving problems such as performing confirmatory factor analysis and identifying the interrelationships of variables in a model. It can simultaneously estimate and evaluate a set of interdependent relationships among the latent variables in a model. This kind of modeling is an adequate method for analyzing causal relationships between latent structures

Table 2 Definition and abbreviation of observed variables examined in the modelling process

Variable Definition (five-point ordinal scale from strongly agree to strongly disagree)	Abbreviation
Environmental characteristics	
Cold temperature causes more covid-19 spread	Coldness
The higher the population density, the higher the transmission of the covid-19	Density
The slope keeps me from using the bike	Slope
Health protocols	
I do not use a bicycle due to difficulty breathing with a mask while cycling	Hard Breath
Cycling violates social distance	Violation
Banning private car usage will increase the use of bicycle	Prohibition
Social distancing cause more private usage and I do not cycle in traffic jams	Crowd Street
Cycling is part of my trip and I have to travel the rest of the way by public transport, But due to social distancing I prefer to travel the whole trip by car	Whole Trip
Self-health protocols	
If shared bikes were disinfected by the company after each use, I would use them	Clean
I do not use devices that someone has used before	Second hand
I think people who use shared bikes are not hygienic	Hygiene
Cycling reduces my stress during the covid-19	Stress
Cycling is an excuse to increase health and wellness	Healthiness
Cycling is the main way to exercise	Main Way

and observable variables that estimates their variance and covariance and performs confirmatory factor analysis. Participants were instructed to respond with strongly agree to strongly disagree to questions on each topic, and one error term was assigned to each variable. The formula for the CFA is as follows [65]:

$$x = \Lambda x \xi + \delta$$

where, x represents the observed variables, ξ represents latent variables, Λx represents coefficients or factor loadings that connect latent and observed variables and δ represents any measurement errors. Typically, the model for this equation is found in a diagram where the latent variable is connected to multiple observed variables. Using this formula, specialists can identify if their model is viable or not. For ease of computation, entire modeling process is carried out using AMOS 24. In structural equation modeling, the number of constructs is called the latent classed and the formula for estimating that is as follow [66, 67]:

$$P(Y = y) = \sum_{x=1}^{c} P(X = x)P(Y = y|X = x)$$

Here, P (Y = y), is a weighted average of the C class-specific probabilities P (Y = y|X = x).

4 Cycling Behavior Analysis

The validity of the questionnaire was assessed using factor load indices and convergent validity. Combined reliability tests and Cronbach's alpha were used to evaluate the reliability of the variables. The results are shown in Table 3. Factor loads are estimated by calculating the correlation value of the indices of a particular structure with that structure. If this value is equal to or greater than 0.4, it confirms that the variance between the structure and its indices is more than the variance of the measurement error of that structure, which indicates that the measurement model is valid. The minimum amount of factor load was determined to be at least 0.4. In addition to Cronbach's alpha, the composite reliability method was used to measure reliability. Since Cronbach's alpha is a traditional criterion to determine the reliability of a structure, the partial least squares method employs a more modern criterion called composite reliability. Its advantage over Cronbach's alpha is that it calculates the reliability of structures according to the correlation of their structures with each other. If the value of combined reliability is more than 0.7, it indicates that the internal stability of the measurement models is appropriate. Cronbach's alpha correlation coefficient is a measure of the

Table 3 Results of confirmatory factor analysis: Evaluation of validity and reliability of variables

Exogenous variables	Mean variance extracted	Composite reliability	Cronbach's alpha	Indicator	Standard coefficient (factor load)
Environmental characteristic	0.70	0.86	0.87	Coldness	0.87
				Density	0.78
				Slope	0.85
Health protocols	0.50	0.82	0.79	Hard Breath	0.58
				Violation	0.58
				Prohibition	0.86
				Crowd Street	0.82
				Whole Trip	0.65
Self-health protocols	0.48	0.910	0.87	Clean	0.72
				Second hand	0.60
				Hygiene	0.69
				Stress	0.59
				Healthiness	0.87
				Main Way	0.89

All factor loads are significant at 95% confidence level: ($p < 0.05$) and ($t < 1.96$)

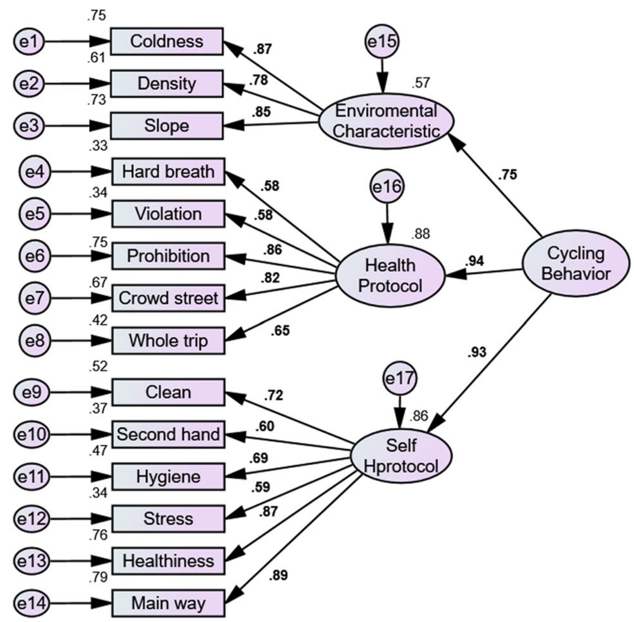


Fig. 2 Final confirmatory factor analysis (standard coefficients)

reliability of internal stability. Similar to factor analysis, internal stability reliability can be employed to observe the intensity of correlations. Using Cronbach's alpha coefficient is the most common method of calculating reliability which was used more than other methods. The general rule is that the value of Cronbach's alpha for a particular scale should be at least 0.7. In the case of AVE, the critical value is 0.5; That is, AVE values higher than 0.5 indicate acceptable convergent validity the [68].

Cochran formula for estimating acceptable sample size is as follows [69]:

$$n0 = (t)2^*(p)(q)/(d)2 = 384$$

where, n0 is the sample size, t is the value for the selected alpha level, e.g. 1.96 for (0.25 in each tail) a 95 percent confidence level. p is the estimated proportion of an attribute that is present in the population. q is 1-p. (p)(q) are the estimate of variance. d is the acceptable margin of error for proportion being estimated, so the confidence interval, in decimals.

Figure 2 shows the final cycling behavior model with 35 parameters and a degree of freedom of 74. For identification purposes, one of the indicators for every latent variable equals the unstandardized coefficient of 1 [70].

5 Results

The results show that obtained factor loads should have a minimum value of 0.40 and be at a significant level less than 0.05 ($p < 0.05$). All t values are greater than 1.96. Therefore, construct validity is confirmed for the questions, all of which have a factor load greater than 0.40. The composite reliability value varied from a minimum of 0.82 for the health protocol to a maximum of 0.91 for the self-health protocol, which is greater than the value of 0.70 for the combined protocol. These reliability values, which are the confirmed values, indicate that the reliability of the scale of research variables is statistically confirmed. Moreover, Cronbach's alpha values ranged from a minimum of 0.79 for the health protocol to a maximum of 0.87 for the environmental characteristics and the self-health protocol scales, indicating that the reliability of the internal matching method is confirmed. Table 3 shows the results of the confirmatory factor analysis.

The final analysis shows that *Health protocol* has the highest weight concerning *cycling behavior* (0.94-factor load), confirming the idea that adherence to health protocols such as mask-wearing or social distancing could be a reason for the decline in using the bicycles for travel. The *Health protocol is followed by the self-health protocol* with a factor load of 0.93, which seems to confirm the hypothesis that although people know that cycling promotes health, they tend not to use shared bicycles in terms of the covid-19virus pandemic. So, a study of the *health protocol* can determine the influence of vehicle traffic prohibition laws *(prohibition*), not driving on crowded streets *(crowded streets),* and three other variables on *cycling behavior*.

The results show that *slope* can have a strong effect on *environmental characteristics* as well as *coldness.* This finding confirms that cold weather and steep street slopes are some of the reasons for not going on cycling trips. Furthermore, *coldness* and *slope* could have a higher negative impact on cycling for females since more women cited high slope areas and cold weather as obstacles to cycling.

According to the results, *cycling is the main way to exercise (main way), which has* the highest factor load of 0.89, indicating a strong relationship with the *self-health protocol* variable. Moreover, analyzing this indicator could

Table 4 Model fit indexes

Indexes	Acceptable range	results
Goodness-of-fit	> 0.90	0.93
Root mean square error of approximation	< 0.08	0.07
comparative fit	> 0.90	0.92
Normalized fit	> 0.90	0.87
Incremental fit index	> 0.90	0.91
adjusted goodness-of-fit	> 0.50	0.73
Parsimony goodness-of-fit	> 0.50	0.68
chi-square/degree of freedom	5 ≥ index ≥ 1	3.35

help determine the factors influencing *the self-health protocol. Regarding factor load, the main way* is followed by *healthiness,* which indicates that cycling contributes to health.

The mean extracted variance, which measures convergent validity, ranged from a minimum of 0.48 for the self-health protocol to a maximum of 0.70 for environmental characteristics. The obtained values confirm the convergent validity of all of the variables The mean variance extracted from the self-health protocol scale is close to the standard value of 0.50 and because the values of factor loads, combined reliability, and Cronbach's alpha for this scale are appropriate, the extracted mean value of variance was confirmed with a little bit of consideration. Overall, the results demonstrate the validity and reliability of the research variables.

Numerous goodness-of-fit measures were considered, as can be seen in Table 4. The root-mean-square error of approximation where the goal is for the population to have an approximate or close fit with the model, rather than an exact fit (RMSEA) for the final model is 0.073, which is under the acceptable value of 0.08. Moreover, the normalized fit (NFI) index is 0.87, which is acceptable with a little bit of consideration. Comparative Fit Index (CFI) that measures the goodness of fit of the hypothesized model compared to a baseline model is in acceptable range. CHI-SQUARE that is in the acceptable range, shows the acceptable overall model fit. Parsimony goodness-of-fit shows the model has great explanatory predictive power.

6 Conclusion

It was found that the use of shared bicycles has decreased in terms of the adherence to health protocols. This finding suggests that regularly disinfecting shared bicycles encourages their use.

Moreover, the results show that policies, such as social distancing restrictions and not disinfecting the bikes after each use can greatly affect cycling behavior and reduce bicycle use. On the other hand, public sensitivity to health issues can affect cyclist behavior, which was the most significant finding of this research. In the confirmatory factor analysis, three latent variables were defined, which were connected to the main latent variable (cycling behavior). Moreover, it was shown that some variables directly affect cycling behavior while the impact of others was determined to be indirect.

However, there were some restrictions on conducting the research. Regarding social distancing laws, it was not possible to interview participants in person, and the survey had to be conducted online, which sometimes leads to inaccurate results. On the other hand, since some people lack the experience of cycling in the city, it was practically impossible for them to answer the questions. Another problem is the ban on women's cycling in the country, which is a major deterrent and might lead to inaccurate outcomes.

Therefore, the issue can be re-examined in another country where circumstances are different. Other issues that can be considered are cycling behavior at younger ages during pandemics as well as the impact of culture and religion on cycling behavior, for instance, the role of religious restrictions in discouraging women from cycling.

In this paper, we have chosen some latent variables and their factor loads of *cycling* and every acceptable factor load represents that it may have a good influence on the cycling rate. Next step is using a structural equation modeling that would be our following work to do.

Appendix

Table 5 Factors associated with cycling in previous studies

Number of reference	Individual characteristics					Trip Characteristics			Population density				Natural Environment Characteristics		Work condition		Latent variable		
	Age	Snack time	Gender	Obesity	Don't like cycling at all	Travel time	Trip distance	recreational	Low/high population	Home location	Traffic flow	Physical effort	Rainfall	Temperature	Employment status	Work hours	Convenience	Social norms	Cycling ability
8							●												
12	●		●																
13	●																		
14	●											●							
15	●		●																●
16	●																		
17		●	●																
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Data Availability The participants of this study did not give written consent for their data to be shared publicly, so due to the sensitive nature of the research supporting data is not available.

Declarations

Conflict of Interest The authors declare that they have no conflict of interest.

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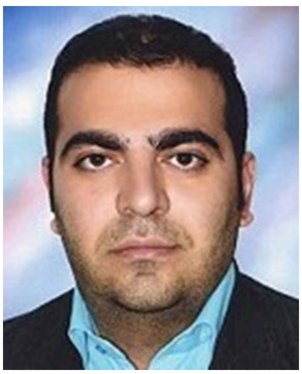

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