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# Finding effective parameters for mitigating traffic congestion near universities

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**This paper intends to assess the effect of different parameters on traffic congestion around universities. On the basis of the model outputs, it is possible to propose economic countermeasures for reducing traffic congestion, especially in developing countries. Structural equation modelling was used to assess the relevance between characteristics of students, features of different modes, environmental conditions and daily demand variations with traffic congestion. The Shahid Bahonar University of Kerman in Iran was considered as a case study. The results showed that it is necessary to decrease the demand first. For this purpose, rescheduling courses is essential to distribute classes more effectively within a week. Virtual classes can be used more frequently as a substitute for traditional on-campus courses. The probability of using buses should be increased by reducing waiting time and fares, and promoting their safety. Similarly, taxi use can be increased by improving safety and waiting time. To reduce the likelihood of using private cars, pricing strategies must establish more limitations for using university carparks.**

**Keywords:** public policy/statistical analysis/UN SDG 11: Sustainable cities and communities

## 1. Introduction

Currently, the population, passenger car ownership and trips in urban streets have risen tremendously, and it is expected to observe more populated cities worldwide. The United Nations has reported rapid urbanisation, and urban population has increased from 751 million in 1950 to 4.2 billion in 2018 (Lu *et al.*, 2021). By 2050, ~70% of the world's population will be predicted to live in cities (Alvarez *et al.*, 2017). Therefore, traffic congestion and its adverse side-effects such as increasing delays, fuel waste, decreasing accessibility and mobility, air pollution, noise pollution, aggressive driving behaviour and travel inconvenience would remain the most challenging issues in metropolitan cities. Traffic congestion is a critical infrastructural deficiency of roads worldwide (Jones *et al.*, 2014). It is forecasted that traffic congestion will worsen in the future (Agyapong and Ojo, 2018; Alvarez *et al.*, 2017; Kiunsi, 2013; Lu *et al.*, 2021).

Prominent universities are among the organisations, which attract numerous visitors each day and confront jam densities during peak hours. Demand management can be investigated through the study of student commuters, as they form a large chunk of each university and have more flexible mode choices (dell'Olio *et al.*, 2019; Nadimi *et al.*, 2021a). Volosin *et al.* (2014) concluded that travel patterns of students differ from other university commuters and must be considered separately for transportation planning programmes. Khattak *et al.* (2011) reported that the travel behaviours of students are not understood in the right manner.

To propose countermeasures to decrease traffic congestion near universities, first, it is necessary to understand the travel behaviours of students (Nadimi *et al.*, 2021a; Nordfjærn *et al.*, 2019; Zhan *et al.*, 2016). Different studies assessed the mode choice behaviours among university students. Nguyen-Phuoc *et al.* (2018) evaluated transportation choices of university students in Vietnam to understand travel patterns and attitudes towards mass transit. The results showed that choice of transportation systems of university students could be remarkably affected by their age, gender and earnings. Moreover, the efficiency and reliability of public transit systems attract students who travel on a motorcycle to public transit (Nguyen-Phuoc *et al.*, 2018). A study carried out by Akar *et al.* shows that the accessibility of facilities related to bicycles plays a vital role in female bicycle usage (Akar *et al.*, 2013). A comparison between male and female students, carried out by Zhou (2016), shows that the former group has taken the lead from the latter in using bicycles or walking to reach the university. Furthermore, undergraduate students are pioneers in this



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regard (Zhou, 2016). Public transportation can be more appealing than cars for students if the bus travel time decreases (Danaf *et al.*, 2014).

Whalen *et al.* (2013) investigated the effects of parameters such as pricing, individual tendencies and street and walkway congestion on mode choice behaviours among the students of McMaster University. Nordfjærn *et al.* (2019) assessed the impact of situational factors, transport priorities and norm activation model on university trips during winter at the Trondheim University of Norway. The results indicated that situational factors were more critical for mode choice decisions compared with psychological variables (Nordfjærn *et al.*, 2019). Haggar *et al.* (2019) tried changing travel mode choices of students in the UK by changing their habits. They concluded that making new travel mode choices is more prevalent among students who have recently shifted their homes (Haggar *et al.*, 2019). Balsas (2003) and Nadimi *et al.* (2021b) evaluated how students can be attracted to more sustainable modes of transportation. To persuade students to utilise bicycles or walk to the university, various essential techniques such as transportation demand management, control, training, provision of facilities and planning were proposed (Balsas, 2003; Nadimi *et al.*, 2021a).

Overall, a review of earlier research reveals numerous studies about the mode choice behaviours of students. However, there is a lack of research concerning the impact of different variables on the traffic congestion near universities, especially in developing countries. This paper aims to propose a method to answer two main questions simultaneously. The first question is how characteristics of students, transportation mode details and environmental conditions affect their mode choice behaviours. The second question is how mode choice behaviours of students, demand variations and time influence traffic congestion near universities. Structural equation modelling (SEM) is used to pursue these objectives. As these two phases have interrelationships, using SEM, it is possible to evaluate these interactions simultaneously.

This study was carried out before the coronavirus disease-2019 (COVID-19) outbreak, and the results were applicable for that period. In addition, the focus was on developing countries with low income that must try to provide economic countermeasures for transport-related issues. This paper follows a methodology that models traffic congestion near universities. Details on obtaining the required data set are also presented. The findings and their interpretation are described in Sections 3 and 4, followed by the conclusion.

## 2. Method

This study made an attempt to develop a model to understand the relationship between the characteristics of students, the features of each transportation mode, environmental conditions and the utility of different modes of travel. The other purpose of the model is to find the impact of mode choice behaviours, demand variation and time on traffic congestion in front of universities.

This study utilises SEM to solve this problem. There are two main reasons for applying SEM in this study. First, traffic congestion has been considered a latent variable (construct) measured by observed variables. Traffic congestion is regarded as traffic irregularities that involve different modes. In addition, there are other latent variables, such as characteristics of students and the details about transportation modes in the model. The second reason relates to the complicated interrelationships among variables in behavioural models. Regarding these relationships, a better understanding of the contributing factors to mode choice behaviours and traffic congestion formation can be provided (Amiri *et al.*, 2021). SEM can also determine the relationships between dependent, independent, latent and observed variables (Amiri *et al.*, 2021; Sheykhfard *et al.*, 2021). SEM has been involved in various behavioural studies (Eboli and Mazzulla, 2012; Gim, 2019; Lin, 2020; Nadimi *et al.*, 2020, 2021b; Sadia *et al.*, 2018; Sheykhfard and Haghighi, 2020; Sheykhfard *et al.*, 2021; Tavakoli Kashani *et al.*, 2021; Zong *et al.*, 2019).

Besides latent and observed variables, endogenous, exogenous or mediator are the three other variables in SEM. An exogenous variable is not only changed or determined by its connection with parameters of another model, but its value is also determined outside the model and then imposed. Endogenous variables are determined or changed by their association with other variables in the model. Mediators try to make a relationship between endogenous and exogenous variables (Najaf *et al.*, 2018).

In this paper, characteristics of students, features of each mode (commuting to the university by buses, taxis, passenger cars, car-pooling and cycling) and environmental conditions are latent exogenous variables. These variables were named students' factor (SF), bus factor (BF), taxi factor (TF), bicycle factor (BIF), passenger car factor (PCF) and car-pooling factor (CPF). These factors were measured by the observed variables presented in Tables 1–6, respectively. Confirmatory factor analysis (CFA) was used to verify these factors statistically.

The mediators in the model are the probability of using a bus (BP), taxi (TP), bicycle (BIP), passenger car (PCP) and car-pooling (CPP) for university trips in different situations. To determine the probabilities, binary logistic regression is used. Binary logistic regression is applicable whenever the dependent variable is 0 or 1. It is intended to determine the probability of



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Table 1. Observed variables related to SF

| Variable | Categories or ranges | Name |
|---|---|---|
| Gender | Male<br>Female | $SF_1$ |
| Age | 18–50 | $SF_2$ |
| Monthly income: US$ | <20<br>20–50<br>50–100<br>100–300<br>300–500<br>>500 | $SF_3$ |
| Having driving license | No<br>Yes | $SF_4$ |
| Accessibility of private cars during a week | 0–5 | $SF_5$ |
| Having a bicycle | Yes<br>No | $SF_6$ |
| Education level | Bachelor of Science (B.Sc.)<br>Master of Science (M.Sc.)<br>Doctor of Philosophy (Ph.D.) | $SF_7$ |
| Period of education | Freshman<br>Sophomore<br>Junior<br>Senior | $SF_8$ |
| Number of weekly trips to the university | 0–5 | $SF_9$ |

using or not using each mode based on the specifications of each mode and characteristics of students (Tables 1–6). A survey form was prepared as presented in the Appendix for this purpose. A binary logistics regression model was constructed for each mode, and the probabilities were calculated. The binary logistic models are run in SPSS Statistics 17.0 to calculate the predicted probabilities for each student.

The total number of students entering the university at each time (ENS), the total number of students who exit the university at each time (EXS), the total number of vehicles that pass through the street in front of the university (PV), day (DY), month (MN) and hour (HR) are the observed exogenous variables in the model.

The latent endogenous variable in the model is traffic congestion. This variable is measured by observed endogenous variables, as presented in Table 7.

A comprehensive questionnaire was used to calibrate the model by interviewing 1600 students at the Shahid Bahonar University of Kerman (SBUK), Iran, between September 2018 and January 2019 (before the COVID-19 outbreak). SBUK, one of the largest universities in the Middle East and North Africa (MENA) and occupies 5 million $m^2$. The university currently has ~12 000 students. The most popular procedure of the partial least squares (PLS)-SEM method for determining the sample size is the '10 times rules'. This rule means that the

Table 2. Observed variables related to BF

| Mode of transportation | Effective parameters | Categories | Name |
|---|---|---|---|
| Bus | Frequency of using buses for university trips previously | Very high<br>High<br>Medium<br>Low<br>Very low | $BF_1$ |
| | Fare amount: cents | Free<br>2–4<br>4–6<br>6–8<br>8–10<br>>10 | $BF_2$ |
| | Safety – number of bus crashes during a year | 0<br>1–3<br>4–6<br>7–9<br>9–11<br>>11 | $BF_3$ |
| | Waiting time: min | <5<br>5–10<br>10–15<br>15–30<br>30–45<br>>45 | $BF_4$ |
| | Ratio of passengers to seats | <0.3<br>0.3–0.6<br>0.6–1<br>>1 | $BF_5$ |
| | Convenience and comfort | Excellent<br>Good<br>Moderate<br>Bad<br>Awful | $BF_6$ |

Table 3. Observed variables related to TF

| Mode of transportation | Effective parameters | Categories | Name |
|---|---|---|---|
| Taxi | Frequency of using taxis for university trips previously | Very high<br>High<br>Medium<br>Low<br>Very low | $TF_1$ |
| | Fare amount: cents | <5<br>5–10<br>10–15<br>>15 | $TF_2$ |
| | Safety – number of taxi crashes during a year | 0<br>1–2<br>3–4<br>5–6<br>>6 | $TF_3$ |
| | Waiting time: min | <5<br>5–10<br>10–15<br>15–30<br>>30 | $TF_4$ |



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Table 4. Observed variables related to BIF

| Mode of transportation | Effective parameters | Categories | Name |
|---|---|---|---|
| Cycling | Frequency of cycling to university previously | Very high<br>High<br>Medium<br>Low<br>Very low | $BIF_1$ |
| | Weather condition | Good<br>Moderate<br>Adverse | $BIF_2$ |
| | Safety – per cent of distance with a thoroughfare for bicycles (from home to university) | 100<br>80–100<br>60–80<br>40–60<br>20–40<br><20 | $BIF_3$ |
| | Bicycle parking distance to destination: m | <100<br>100–400<br>400–600<br>600–800<br>>800 | $BIF_4$ |
| | Monthly financial savings due to using a bicycle: US$ | >10<br>4–10<br>2–4<br>1–2<br><1 | $BIF_5$ |
| | Distance between the origin and university: km | <1<br>1–2<br>2–3<br>3–4<br>4–5<br>5–8<br>8–12<br>>12 | $BIF_6$ |

Table 5. Observed variables related to PCF

| Mode of transportation | Effective parameters | Categories | Name |
|---|---|---|---|
| Passenger car | Frequency of using passenger cars for university trips previously | Very low<br>Low<br>Medium<br>High<br>Very high | $PCF_1$ |
| | Parking charge: cents/h | >20<br>15–20<br>12–15<br>8–12<br>5–8<br>2–5<br>Free | $PCF_2$ |
| | Chance of parking availability: % | <10<br>10–20<br>20–30<br>30–50<br>50–70<br>>70 | $PCF_3$ |

Table 6. Observed variables related to CPF

| Mode of transportation | Effective parameters | Categories | Name |
|---|---|---|---|
| Car-pooling | Using car-pooling for university trips previously | Very high<br>High<br>Medium<br>Low<br>Very low | $CPF_1$ |
| | Daily costs of car-pooling: cents | <5<br>5–7<br>7–10<br>10–15<br>15–20<br>20–50<br>>50 | $CPF_2$ |
| | Probability of parking availability: % | >70<br>50–70<br>30–50<br>20–30<br>10–20<br><10 | $CPF_3$ |
| | Availability of proper partners | Always<br>Often<br>Usually<br>Occasionally<br>Rarely | $CPF_4$ |

Table 7. Observed variables related to traffic congestion factor

| Observed variables | Details | Name |
|---|---|---|
| Passenger cars' density | Ratio of passenger car demand to available parking lots at each time | PCD |
| Buses' density | Ratio of bus demand to bus stops at each time | BD |
| Taxis' density | Ratio of taxi demand to the number of locations considered for taxi stands at each time | TD |
| Shared-cars' density | Ratio of shared car demand to available parking lots devoted to them at each time | CPD |
| Volume to capacity | Volume of traffic in the street in front of the university to its capacity | V/C |
| Vehicles' density | Ratio of the total demand for vehicles at each interval to the available area in front of the university | VD |

suitable sample size is more significant than 10 times the maximum number of inner or outer model links concerning the latent variables in the SEM. The total number of links is 78, and thus the sample size must be greater than 780 (Kock and Hadaya, 2018).

In this paper, interviews were conducted with 1600 SBUK students. To have a representative sample, student interviews were conducted with fairly different characteristics. Different scenarios were formulated based on Tables 2–6, and they



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questioned if a student would use or not use each mode under a given circumstance. Then with the aid of binary logistic regression, the probability of using each mode in each case is calculated.

The PLS method is acclaimed for its soft modelling technique, which was developed by Herman Wold in the mid-1960s. In this method, the number of required cases can be reduced due to its ability to fit each part of the model individually (Wong, 2019). To apply the PLS method in SEM modelling, SmartPLS is used, a software with a graphical-user interface.

The model outputs can help practitioners establish suitable countermeasures to reduce the traffic congestion in front of universities. These countermeasures work on travel behaviours of students to reduce the demand for passenger cars.

## 3. Results

In this section, SEM outputs will be presented, and then the reliability, validity and model goodness of fit (GoF) will be discussed.

### 3.1 SEM output

Figure 1 shows the calibrated SEM. There are two numbers above each arrow in the SEM. One is within parentheses, and the other is not. These numbers represent standard path coefficients and *T* values for each variable, respectively. The path coefficients close to 1 indicate a strong relationship. In addition, *T* values greater than 1.96 and 1.64 indicate that the results are significant at 0.05 and 0.1 levels, respectively.

According to the results (Figure 1), TP, CPP, PCP, BIP, BP, ENS, EXS and PV significantly affect traffic congestion near SBUK.

### 3.2 Model assessment

To evaluate the model outputs, the validity and reliability of the measurement model and the reliability of observed variables (for each CFA) were analysed. The GoF of the model was also investigated.

Cronbach's $\alpha$ assesses the convergent accuracy and reliability of the model. The acceptable Cronbach's $\alpha$ and composite reliability values are usually greater than 0.7. The average variance extracted (AVE), as the convergent validity index, is applied to measure the accuracy of the measurement model. AVE greater than 0.5 is considered to be acceptable (Chin, 1998; Esposito Vinzi *et al.*, 2010; Henseler and Sarstedt, 2013).

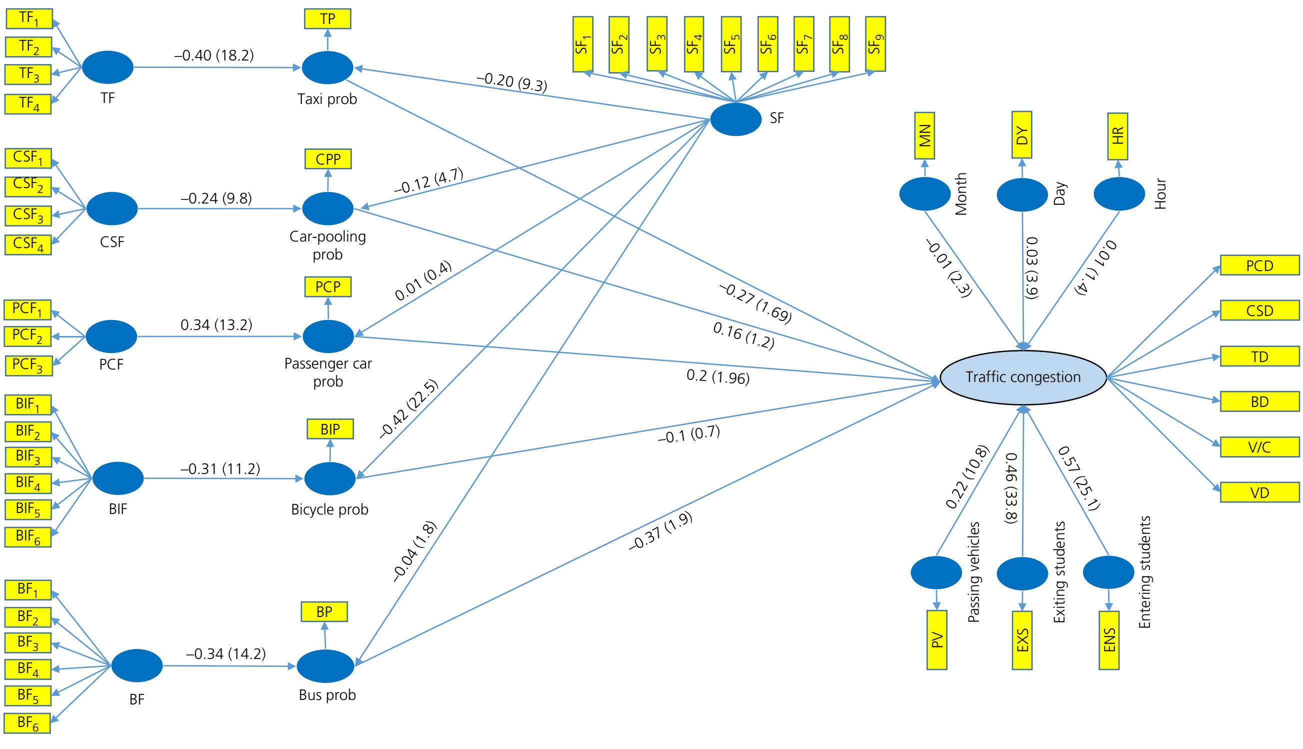


Figure 1. Calibrated SEM model



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Table 8 shows the values of measurement models such as AVE coefficients, Cronbach's $\alpha$ and composite reliability.

As demonstrated in Table 8, the composite reliability coefficient can confirm the internal consistency of latent variables. The internal consistency of the model can be approved based on the Cronbach's $\alpha$ values. Nonetheless, this metric is less valid than composite reliability as it does not consider the changing factor loadings of the items. In addition, as all AVEs are higher than 0.50, the validity of the measurement model can be approved.

Discriminant validity is another form of validity that needs to be controlled in SEM. Discriminate validity implies that the correlation between observed variables of each latent variable must be controlled with other latent variables and their observed variables. The correlations between the observed variables and related latent variable should be close to 1, whereas the correlations between the observed variables of different latent variables should be close to 0. Considering the number of measures and constructs in our SEM model, the details of discriminant validities were not shown, but the results were satisfactory.

Table 8. Outputs of model reliability and validity by AVE, Cronbach's $\alpha$ and composite reliability

| Latent variables | Cronbach's $\alpha$ | Composite reliability | AVE |
|---|---|---|---|
| Traffic congestion | 0.97 | 0.95 | 0.94 |
| SF | 0.89 | 0.9 | 0.87 |
| PCF | 0.76 | 0.92 | 0.73 |
| CPF | 0.70 | 0.9 | 0.69 |
| BIF | 0.61 | 0.81 | 0.56 |
| TF | 0.72 | 0.71 | 0.71 |
| BF | 0.67 | 0.86 | 0.65 |

On the basis of factor loadings and the significance of each variable, the reliability of observed variables, using path coefficients and $T$ values of each variable are controlled. The path coefficients must be close to 1, and $T$ values must be higher than 1.96 and 1.64 for significant levels of 0.05 and 0.1, respectively (Chin, 1998). Table 9 presents the details of $T$ values and loading factors.

As shown in Table 9, $BF_5$ is not significant. According to the results, all the variables are acceptable at the 0.05 significant level, except for $BF_1$, which was found acceptable at the 0.1 significant level. The loading factors are also acceptable as they are all more than 0.4.

The model goodness was assessed by using GoF index. GoF index is useful to assess the global validity of an SEM model. The GoF of the substantial, moderate and weak models was equal to 0.36, 0.25 and 0.01, respectively. In this study, GoF was 0.35, indicating that the GoF of the model is satisfactory.

## 4. Discussion

The SEM outputs indicated that the most significant factors in traffic congestion in front of SBUK are the number of students who enter or exit the university at each interval. This means that before suggesting a plan to attract students to use different modes of transportation, the demands of students should be managed first. On the basis of the survey forms, more than 80% of students commute to SBUK to attend classes. Currently, the course schedules are designed based on other criteria, and traffic issues are neglected. Distribution of courses at different time intervals during the week is necessary to reduce traffic congestion. For this purpose, the traffic demand outside the university must also be considered (PV).

Table 9. Loading factors and $T$ values of SEM

| Latent variables | Observed variables | Loading factor | $T$ value | Latent variables | Observed variables | Loading factor | $T$ value |
|---|---|---|---|---|---|---|---|
| SF | $SF_1$ | 0.907 | 44.23 | BIF | $BIF_1$ | 0.961 | 33.2 |
| | $SF_2$ | 0.429 | 2.24 | | $BIF_2$ | 0.408 | 2.09 |
| | $SF_3$ | 0.618 | 4.17 | | $BIF_3$ | 0.441 | 2.3 |
| | $SF_4$ | 0.765 | 20.95 | | $BIF_4$ | 0.611 | 3.25 |
| | $SF_5$ | 0.798 | 15.37 | | $BIF_5$ | 0.413 | 1.98 |
| | $SF_6$ | 0.494 | 6.76 | | $BIF_6$ | 0.634 | 4.26 |
| | $SF_7$ | 0.618 | 4.17 | TF | $TF_1$ | 0.887 | 14.4 |
| | $SF_8$ | 0.615 | 9.69 | | $TF_2$ | 0.433 | 4.5 |
| | $SF_9$ | 0.501 | 10.61 | | $TF_3$ | 0.643 | 8.1 |
| | | | | | $TF_4$ | 0.644 | 9.5 |
| BF | $BF_1$ | 0.553 | 1.95 | CPF | $CPF_1$ | 0.816 | 6.47 |
| | $BF_2$ | 0.762 | 6.34 | | $CPF_2$ | 0.748 | 6.87 |
| | $BF_3$ | 0.736 | 5.73 | | $CPF_3$ | 0.748 | 2.94 |
| | $BF_4$ | 0.905 | 8.87 | | $CPF_4$ | 0.632 | 5.44 |
| | $BF_5$ | 0.428 | 1.57 | PCF | $PCF_1$ | 0.656 | 6.65 |
| | $BF_6$ | 0.679 | 6.37 | | $PCF_2$ | 0.473 | 5.86 |
| | | | | | $PCF_3$ | 0.848 | 6.37 |



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The university can also present a portion of courses through online teaching besides the traditional on-campus classes to decrease the presence of students at the university.

Among different transportation modes, buses, taxis and passenger cars have the highest effect on traffic congestion. As the probability of using buses increases, traffic congestion decreases. The characteristics of students did not have any effect on bus usage increment. However, the specifications of buses can influence their utility. Waiting time, fare amount and perceived safety are the most critical variables, increasing the probability of using buses for university trips.

Taxi is the second important transportation mode, which can decrease traffic congestion in front of SBUK. Unlike buses, both characteristics of students and specifications of taxis influence the improvement in the traffic situation around the university. If a student uses taxis more frequently, then the probability of using this mode in the future would also be higher. Waiting time is the second important factor influencing using taxis for university trips. The perceived safety of taxis also has the same impact as waiting time on changing the probability of using this transportation mode.

An increase in the probability of using passenger cars would increase traffic irregularities in front of the university. This issue relates to the fact that the average number of students who commute by car on each trip is less than two. The characteristics of students do not affect the probability of using passenger cars for university trips. Nevertheless, the chance of finding proper parking, being accustomed to passenger cars for daily trips, and parking costs have the highest impacts on using passenger cars.

Day, month and time did not influence traffic congestion. This relates to the demand stability of students throughout a year, a week and a day.

## 5. Conclusion

Traffic congestion is a serious concern in metropolitan cities, and it is more evident around large organisations such as universities. This paper proposes a new method to assess the impact of different variables on traffic congestion in front of universities. The concentration was directed at travel behaviours of students in the models. Students are the primary group in the university and have more potential to choose different modes for university trips. Therefore, it is easier to decrease traffic congestion by studying the travel behaviours of this group. SEM was applied to determine the link between characteristics of students, specifications of each mode, the probability of using a specific mode, demand and traffic congestion. Passenger cars, buses, taxis, car-pooling and cycling are the target modes for the university trips of students.

The model was tested for a case study in SBUK, Iran. Entering and exiting demands had the highest impact on traffic congestion (with loading factors of 0.46 and 0.57 shown in Figure 1). The abovementioned issue means that before considering supply specifications, it is vital to pay attention to demand management. For this purpose, the education management office must pay attention to the traffic congestion issue when preparing course schedules of each semester. In addition, it seems necessary to present more courses in online teaching instead of the current status.

The likelihood of using buses, taxis and passenger cars has the highest effect on traffic congestion in front of SBUK, respectively (with loading factors of −0.37, −0.27 and 0.2). To increase the probability of using buses, their waiting time must be reduced and should be satisfactory for students (with a loading factor of 0.905). For this purpose, the bus service needs a precise timetable with reasonable headways. Then the proportionality of fare amount with income of students must be considered (with a loading factor of 0.762). Finally, students must feel that the university buses are safe (with a loading factor of 0.736). It was proven that those students who use taxis frequently for university trips are more loyal to this mode in the future (with a loading factor of 0.887). In addition, to increase the probability of using a taxi, its waiting time and perceived safety need to be improved (with loading factors of 0.644 and 0.643).

To decrease traffic congestion, it is necessary to reduce the probability of using passenger cars (with a loading factor of 0.2). Thus, limitations must be considered for parking based on time and duration (with a loading factor of 0.848). For this purpose, cost for parking can be a reasonable countermeasure. SEM outputs also showed that it is challenging to shift transportation mode of students for those who use passenger cars frequently (with a loading factor of 0.656). The issue, as mentioned earlier, means that even increasing the utility of buses or taxis, it is difficult to attract such students, and limitations in using passenger cars might persuade them to switch to a different mode of transport.

The proposed countermeasures to reduce traffic congestion are easy to establish, and at the same time, the benefit-to-cost ratio of each countermeasure is observed. Most of them need a policy and programming without significant changes in transportation infrastructures.

The theoretical and/or methodological contributions of this paper are not limited to this case study. Although this research



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was carried out for a specific case study, identifying the impact of different variables on traffic congestion in front of major organisations by using SEM and the concept of the proposed model are novel and can be used for other case studies as well. For each organisation with traffic congestion around it, the same method can be applied to determine the relationship between characteristics of passengers, the specifications of each mode, environmental parameters, mode choice behaviour, demand variations and traffic irregularities. Thus, this model can be used for each country with relevant data.

Nevertheless, it is possible to consider other transportation modes for each model with different variables associated with it based on the condition of that case study. In addition, it is possible for each country to consider different observed variables for traffic congestion as the latent variable. Moreover, for each transportation mode, it is possible to consider different effective characteristics based on each case study.

## Appendix: Survey form

### Part 1. General questions

(1) Gender
    Male
    Female
(2) Monthly income or the money received from family (US$)
    Less than 20
    20–50
    50–100
    100–300
    300–500
    > 500
(3) Having driving license
    No
    Yes
(4) Number of days with access to a private car during a week
    0
    1
    2
    3
    4
    5
(5) Do you have a bicycle?
    No
    Yes
(6) What is your education level?
    Bachelor of Science (B.Sc.)
    Master of Science (M.Sc.)
    Doctor of Philosophy (Ph.D.)
(7) What is your stage of education?
    Freshman
    Sophomore
    Junior
    Senior
(8) How many weekly trips do you have to the university?
    0
    1
    2
    3
    4
    5
(9) Frequency of using the bus for university trips currently?
    Very high
    High
    Medium
    Low
    Very low
(10) Frequency of using a taxi for university trips currently?
    Very high
    High
    Medium
    Low
    Very low
(11) Frequency of cycling to university currently?
    Very high
    High
    Medium
    Low
    Very low
(12) Frequency of using passenger cars for university trips currently?
    Very high
    High
    Medium
    Low
    Very low
(13) Frequency of using car-pooling for university trips?
    Very high
    High
    Medium
    Low
    Very low

### Part 2.1. Using bus probability

In each scenario, please say if you use a bus or not?

(1) Fare amount is free, number of bus crashes during a year is 0, waiting time is less than 5 min, the ratio of passengers to seats is on average less than 0.3, convenience and comfort is excellent.
    No
    Yes
(2) Fare amount is free, number of bus crashes during a year is 1–3, waiting time is less than 5 min, the ratio of



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passengers to seats is on average less than 0.3, convenience and comfort is excellent.
No
Yes

(3) Fare amount is 2–4 cents, number of bus crashes during a year is 1–3, waiting time is less than 5 min, the ratio of passengers to seats is on average less than 0.3, convenience and comfort is excellent.
No
Yes

(Other combinations of variables related to the bus were also posed, but for the sake of brevity they are not presented here).

### Part 2.2. Using taxi probability

In each scenario, please say if you use a taxi or not?

(1) The fare amount is less than 5 cents, the number of taxi crashes during a year is 0 and the taxi waiting time is less than 5 min.
No
Yes

(2) The fare amount is less than 5 cents, the number of taxi crashes during a year is 1–2 and the waiting time for taxis is less than 5 min.
No
Yes

(3) The fare amount is 5–10 cents, the number of taxi crashes during a year is 0 and waiting time for a taxi is less than 5 min.
No
Yes

(Other combinations of variables related to taxis were also posed, but for the sake of brevity they are not presented here).

### Part 2.3. Using bicycle probability

In each scenario, please say if you use a bicycle or not?

(1) The weather condition is good, 100% of the path between home to university has a thoroughfare for bicycles, bicycle parking distance to the destination is less than 100 m, monthly financial savings due to using a bicycle is more than US$10 and the distance between the origin to university is less than 1 km.
No
Yes

(2) Weather condition is adverse, 100% of the path between home to university has a thoroughfare for bicycles, bicycle parking distance to the destination is less than 100 m, monthly financial saving due to using a bicycle is more than US$10 and the distance between the origin to university is less than 1 km.
No
Yes

(3) Weather condition is good, 40–60% of the path between home to university has a thoroughfare for bicycles, bicycle parking distance to the destination is less than 100 m, monthly financial savings due to using a bicycle is more than US$10 and the distance between the origin to university is less than 1 km.
No
Yes

(Other combinations of variables related to bicycles were also posed, but for the sake of brevity they are not presented here).

### Part 2.3. Using passenger car probability

In each scenario, please say if you use a passenger car or not?

(1) The parking charge per hour is more than US$20, and the chance of parking availability is less than 10%.
No
Yes

(2) The parking charge per hour is US$15–20, and the chance of parking availability is less than 10%.
No
Yes

(3) The parking charge per hour is more than US$20, and the chance of parking availability is 10–20%.
No
Yes

(Other combinations of variables related to passenger cars were also posed, but for the sake of brevity they are not presented here).

### Part 2.3. Using car-pooling probability

In each scenario, please say if you use a passenger car or not?

(1) Daily costs of car-pooling are less than 5 cents, probability of parking availability is more than 70%, always proper partners are available.
No
Yes

(2) Daily costs of car-pooling are 5–7 cents, probability of parking availability is more than 70%, always proper partners are available.
No
Yes

(3) Daily costs of car-pooling are 5–7 cents, probability of parking availability is 50–70%, always proper partners are available.



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No
Yes

(Other combinations of variables related to car-pooling were also asked, but for the sake of brevity they are not presented here).

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