Response to reviewers

6/20/2020

We wish to thank the two anonymous reviewers for their feedback on the initial version of our paper. In this letter we respond to their comments and describe the changes made to the paper in response. Reviewer comments are in black and our responses in blue.

Editor

Please work on your title, it reads very awkwardly.

> We have changed the title of the paper to "How do the perceptions of neighborhood conditions impact urban active travel? A study in Rajshahi, Bangladesh."

Reviewer 1

- From my experience, people tend to give more weight to personal safety instead of road safety. Very good highlight from the paper: Improving perceptions of crime helps only after other perceptions are improved)

  Many thanks for reading the paper and for sharing your thoughtful suggestions with us.

- Women do not have a large labor participation in Bangladesh, but in many cities, women do more care-mobility trips than work-trips. This care-mobility trips also tend to be made in a neighborhood scale more than a city scale (unlike work-trips). It would be interesting to see if in this study, female responses are similar to male responses.

  Thank you for this comment. We included gender in the model, but it was not significant and it was removed from the analysis to keep the model parsimonious. A reason for this lack of significance can possibly be found in the particular challenges of collecting data in a place where females are often not comfortable sharing information with unknown parties. We have included in this revision some additional discussion of the cultural context and the data collection process to empasize this. We also identify as an avenue for future research the development of effective strategies to conduct surveys that recognize the cultural challenges of data collection in this context.

- Do you have access to the area's crime rates? How is this be related to the answers?
- Do you have access to the area's road crash rates? How is this be related to the answers ?

  Thank you for these questions. In addition to the issues regarding data collection above, another challenge when analyzing travel behavior in the Global South, particularly in some of the poorest countries/regions, is that many types of administrative data are not collected systematically, and even when they are, they are often not available to the public. There are many reasons for this, including that events are not reported because of lack trust on the authorities, or that data are zealously guarded by the authorities to limit accountability. Regardless of the actual reasons, in the present case data on crime and accidents are not available for research. This was, in fact, the rational for asking respondents about their perceptions of safety in the survey. Lacking corroborating information we must consider this a limitation of the study; on the other hand, evidence available from other studies suggests that perceptions are a good proxy for the objective conditions, and in some cases also a superior explanatory variable. Conceptually, this is explained by the comparison theory, which posits that people evaluate their situation in relation to a reference group or historical experience (see Liao, 2009). In this way, Gatersleben and Appleton (2007) found that the intention to cycle changes with perceptions; Cleland et al. (2008) studied walking for leisure and transport from the perspective of perceptions of the social and built environment; Liao et al. (2015) investigated the associations between perceptions of the environment and walking and cycling in Taiwan; and Loo et al. (2015) research on transport modes in Malaysia. Another finding is that perceptions of both the physical and social environment display remarkable geographical coherence (see Whalen et al., 2012; and Paez, 2013), which gives us ground to feel confident in the usefulness of perceptions as a sensible variable in this situation where objective observations of some environmental factors are not available.

Reviewer 2

Thanks for the opportunity to review this paper. This paper addresses an interesting topic, urban active transportation use and its correlates in Rajshahi, a city of a Global South country (Bangladesh). Among the correlates to understand the use of active modes, the authors include attributes of the trip, attributes of the individual, and perceptions of the social and physical conditions of the built environment. The topic of the paper is worthy of research, mostly because it reports a case study in a city of a Global South country, where more studies are needed to understand the particularities in these contexts that are different from the ones reported from the Global North.

> Thank you for your kind words, and thoughtful comments for improving the paper.

However, being the first study on this topic in Bangladesh (as claimed by the authors) should not be the main reason for publishing this paper. I think that the paper should deliver a broader contribution besides of the particularities of the Bangladesh context. What will the readers learn after reading the paper? Are these results generalizable to other Global South contexts? What are the differences in the results of this paper with other literature? Answering some of those questions will help the authors to strengthen the positioning of the paper.

> Thank you for this comment. We have edited the paper in response to this recommendation, and the discussion is now more clear about the context in Bangladesh and also how this study contributes to our understanding of cycling and travel in the Global South.

Also, the authors claim in the abstract that the paper aims to investigate the environmental correlates of urban active transportation, but they rely only on perceptions about social and physical conditions of the built environment. Even though, at the end of the paper, the authors recognize this limitation is maybe one of the main weaknesses. I know that this will be a new project, but incorporating measurable physical characteristics of the built environment in the model to evaluate the association between active mode use and built environment factors should be preferable as perceptions are quite challenging to quantify.

> Thank you for this comment. A challenging aspect of working in one of the poorest regions of the Global South is collecting measurable physical characteristics of the built (and social) environment. This challenge is perhaps even more formidable than collecting perceptions. For example, attributes of the built environment are not collected in a systematic way by relevant authorities; events are not reported by the public because of low trust on the authorities; or data are zealously guarded by the authorities to limit accountability. In contrast, directly asking people about their perceptions is relatively straightforward and is a well-established practice in many fields, including transportation research (see van Acker et al., 2010; and van Acker, 2011). The obvious question is, are those perceptions useful to understand behavior? Here, we are supported by comparison theory (see Liao, 2009), which posits that people evaluate their situation in relative terms to a reference group or historical experience. Furthermore, there is a wealth of research that shows that behavior (what we are ultimately interested in) is influenced by those perceptions. This includes research on active travel both in the Global South and in developed economies (see, inter alia, Gatersleben and Appleton, 2007; Cleland et al., 2008; Akar and Clifton, 2009; Liao et al., 2015; and Loo et al., 2015). Therefore, we feel confident in the usefulness of perceptions as explanatory variables, even while we acknowledge the necessity of objectively measured attributes as well.

Concerning the sample, the authors surveyed 402 commuters. However, there are some issues regarding participant selection and representativeness that should be mentioned in the paper.

- Is the sample representative for the population?

  Table 1 contains the descriptive statistics of the sample. It should be noted that demographic data of the municipality (study area) are not readily available; however, the district level (Rajshahi municipality is under Rajshahi district) age distribution data of 2015 is available and used in this study for comparison purpose (see Bangladesh Bureau of Statistics, 2015). Around 19% of the population belongs to 15 to 24 years age group of Rajshahi district. As the focus of the current study is AT users, the percentage of this group is higher in the sample (39.9%). Additionally, being a city with numerous higher education institutions, this segment of the population represents the major portion of the student population who are the primary users of the active modes of travel (also see Whalen et al., 2013). For the same reason, 26 to 45 age group represents 45% of the sample, although 32.7% of the population belongs to the same age group. Also, the percentage of older adults living in Rajshahi is low. Overall, only 18.9% of the population belongs to 45 years and over. In the study sample, 7.5% belong to the age group 45 years and over. On average, respondents have at least one bicycle at home. Average income among the households is 35,105 BDT (1 USD = 84 BDT). It should be noted that the average household income of the capital city Dhaka is 55,086 BDT (Power and Participation Research Centre, 2016). Forty-two percent of the respondents identified themselves as students, and 37% as full-time employees. A comparison among the population income and occupation group is not possible as up to date city or regional level income and occupation data are not available for Rajshahi. Last available data of Rajshahi city is from a survey of 2001 which is not relevant in the current context as the local conditions (socio-ecomonic conditions, city characteristics, and modal shares) have changed much over the past few years.

There are some important considerations to keep in mind with respect to collecting data in Bangladesh (also see the research of Aslam et al., 2018, in Pakistan). First, participation in out-of-home activities is very low in Bangladesh among females, with a national rate of female labor force participation at only 36.3% (Hossain, 2018). This means that the probability of finding female respondents is relatively low to begin with. Secondly, traditional social norms in Bangladesh mean that males usually respond on behalf of their households, and they are culturally disinclined to share information pertaining to female family members. Even females are often not comfortable sharing their information with unknown parties (also see the research of Mitra, 2016, in Rajshahi). As a result, almost 85% of respondents in this study are male. Thus, the sample cannot be said to be representative of the general population; data collection is a pervading issue in the Global South, and therefore the results should be seen as pertaining to this context.

- How were the participants selected? Please describe the survey process carefully, emphasizing in the data collection procedure.
- Is the sample capturing similar socioeconomic patterns compared to Rajshahi city?
- It seems that the average income in the sample is lower than the average income of Dhaka. Nevertheless, why did the authors compare income with Dhaka and not with the one for Rajshahi?
- Please explain the cleaning process of the sample. Explicitly, state the reasons to eliminate observations .

  There are 30 wards in Rajshahi and the survey targeted to collect an equal number of samples from each ward (the initial target was to collect 10 samples from each ward). A random sampling process was followed while choosing a respondent within a ward, and both complete and incomplete surveys were accepted. As residents were reluctant to participate in the survey, and surveyors noticed the presence of missing information (due to unwillingness of the respondents to share information) among the collected samples, attempts have been made to collect some additional samples. 352 samples were collected from the 30 wards of Rajshahi. In addition to that, the survey collected samples from the people who live in the surrounding areas of the city. Although the exact number/ portion is unknown, it was been noticed that a significant portion of people lives in the surrounding areas of the city who commute daily to the city. Samples were collected from this group of working segments as we think that it is relevant to explore the AT condition of the city. 50 random samples were collected from the surrounding areas who commute daily to the city. Thus, a total of 402 samples were collected through the face-to-face survey. As all questions in the survey were optional, some records had several missing variables, which rendered them unusable. Responses with missing variables were removed and finally, 393 responses with complete set of variables were taken for final analysis.

Regarding the modelling, some issues need to be clarified throughout the document.

- The authors claim the use of a multinomial logistic regression. However, it seems that the model structure is closer to a binary logit than to a multinomial logit. The model compares a given transport alternative with walking, which is used as the base transport mode .
  - How did the authors estimate the model? Please explain if the authors estimated multiple binary logit models or they estimated a multinomial logit considering that each respondent only has two alternatives in every choice situation. If the authors followed the second approach, it would be tough to think that always the respondents only had two alternatives available.

Thank you for these questions. Your comments reveal expertise with discrete choice analysis. The model we use is not a discrete choice or random utility; instead it is a probabilistic. We have edited the text to more clearly explainthis. In order to respond to your suggestions, we draw from Chapter 5 of An Introduction to Discrete Choice Analysis: A Course in R, found here: https://paezha.github.io/discrete_choice_analysis/chapter-4.html.

To more effectively see how the model is multinomial, it is useful to recall the components of a discrete choice model:

$$\text{choice} \sim \text{alternative specific constants} \mid \text{alternative specific vars with generic coefficients} \mid \text{individual specific vars}$$

The alternative specific constants capture any systematic variability not captured by other variables, and often are interpreted as a ranking of preferences between the alternatives. The alternative specific variables refer to level of service attributes, such as travel time by different modes, their cost, etc. These variables are essential for a multinomial model to be a discrete choice model: the unit of analysis is the alternative, and the decision maker is assumed to choose one of the alternatives after comparing their attributes. The individual specific variables describe the decision maker and help to understand heterogeneity among individuals.

Here, we express these components using a concrete example, which is a reduced version of the model we use in the paper (with only one alternative specific variable, say cost, and one individual specific variable, say age; there is no loss of generality here):

$$\begin{array}{llll}
 & \overbrace{\begin{array}{lll} & & \end{array}}^{\text{alternative specific constants}} & & \overbrace{\begin{array}{lll} & & \end{array}}^{\text{individual vars. with specific coefficients}} \\
V_{i\text{Walk}} = & 0 \quad +0 \quad +0 & +\beta_1 \text{cost}_{i\text{Walk}} & 0 \quad +0 \quad +0 \\
V_{i\text{Cycle}} = & \mu_{\text{Cycle}} \quad +0 \quad +0 & +\beta_1 \text{cost}_{i\text{Cycle}} & \gamma_{\text{Cycle}}\text{age}_i \quad +0 \quad +0 \\
V_{i\text{Rickshaw}} = & 0 \quad +\mu_{\text{Rickshaw}} \quad +0 & +\beta_1 \text{cost}_{i\text{Rickshaw}} & 0 \quad +\gamma_{\text{Rickshaw}}\text{age}_i \quad +0 \\
V_{i\text{Car}} = & 0 \quad +0 \quad +\mu_{\text{Car}} & \underbrace{+\beta_1 \text{cost}_{i\text{Car}}}_{\text{alternative vars. with generic coefficients}} & 0 \quad +0 \quad +\gamma_{\text{Car}}\text{age}_i
\end{array}$$

It is a standard condition that one of the alternatives must be selected as a reference both for the alternative specific constants and the individual-level variables for identifiability (since the model works based on the differences between utilities), or as an alternative perspective, to avoid perfect multicollinearity. Given the utility functions, the logit probabilities for each alternative are:

$$\begin{aligned}
&P(\text{Cycle}) = \frac{e^{V_{\text{Cycle}}}}{e^{V_{\text{Cycle}}}+e^{V_{\text{Walk}}}+e^{V_{\text{Rickshaw}}}+e^{V_{\text{Car}}}} \\
&P(\text{Rickshaw}) = \frac{e^{V_{\text{Walk}}}}{e^{V_{\text{Cycle}}}+e^{V_{\text{Walk}}}+e^{V_{\text{Rickshaw}}}+e^{V_{\text{Car}}}} \\
&P(\text{Car}) = \frac{e^{V_{\text{Cycle}}}}{e^{V_{\text{Cycle}}}+e^{V_{\text{Walk}}}+e^{V_{\text{Rickshaw}}}+e^{V_{\text{Car}}}} \\
&P(\text{Walk}) = 1 - P(\text{Cycle}) - P(\text{Rickshaw}) - P(\text{Car})
\end{aligned}$$

It is not always the case that level of service (i.e., alternative-specific) attributes are available. When this is the case, they can be imputed by the analyst, a time consuming and complex process that requires modelling travel times, availability of information such as fares, etc. An alternative, is to change the way the analysis is conceptualized; instead of thinking of the model as a choice process, the model is the probability of a traveler being in a certain state for a trip - what is termed a probabilistic multinomial model. The probabilistic multinomial model is formally equivalent to a choice model without alternative specific attributes. In this case, the utility functions, or more accurately, the latent functions for the different states, take this form:

$$
\begin{array}{lllllll}
 & \multicolumn{3}{c}{\overbrace{\hspace{10em}}^{\text{alternative specific constants}}} & \multicolumn{3}{c}{\overbrace{\hspace{14em}}^{\text{individual vars. with specific coefficients}}} \\
V_{i\text{Walk}} = & 0 & +0 & +0 & 0 & +0 & +0 \\
V_{i\text{Cycle}} = & \mu_{\text{Cycle}} & +0 & +0 & \gamma_{\text{Cycle}}\text{age}_i & +0 & +0 \\
V_{i\text{Rickshaw}} = & 0 & +\mu_{\text{Rickshaw}} & +0 & 0 & +\gamma_{\text{Rickshaw}}\text{age}_i & +0 \\
V_{i\text{Car}} = & 0 & +0 & +\mu_{\text{Car}} & 0 & +0 & +\gamma_{\text{Car}}\text{age}_i
\end{array}
$$

We can inspect any one of these probabilities:

$$
\begin{aligned}
P(\text{Cycle}) &= \frac{e^{V_{\text{Cycle}}}}{e^{V_{\text{Walk}}}+e^{V_{\text{Cycle}}}+e^{V_{\text{Rickshaw}}}+e^{V_{\text{Car}}}} \\
&= \frac{e^{\gamma_{\text{Cycle}} age_i}}{e^{0}+e^{\gamma_{\text{Cycle}} age_i}+e^{\gamma_{\text{Rickshaw}} age_i}+e^{\gamma_{\text{Car}} age_i}}
\end{aligned}
$$

All latent functions corresponding to the different states of the individuals for their trips (i.e., their modes of travel) enter the logit probability formula of every state, which shows that the model is indeed multinomial, and not some sort of pairwise binary model. A reference state (i.e., mode) is selected; all the coefficients are relative to that state. A standard result of this formulation is that it does not matter which state is chosen as a reference, all coefficients simply shift to preserve the same differences between states. Furthermore, since this is not a discrete choice model, no assumptions are made about the choice set.

- Did the authors try to estimate nested logit models? Considering the presence of walking and bicycle, it should be expected to find closer substitution patterns between these alternatives.

  We now turn our attention to the nested logit model. The following discussion draws from Chapter 7 of An Introduction to Discrete Choice Analysis: A Course in R; see: https://paezha.github.io/discrete_choice_analysis/chapter-6.html.

  The utility functions of a nested logit model can be separated into variables that are different within a nest, and those that are identical within a nest:

$$
V_j = Z_j + W_s
$$

  where Z_j are the attributes specific to the alternatives (they vary within the nest), and W_s are attributes specific to nest s (they are constant within the nest).

  The distinction between alternative- and nest-level variables is necessary because attributes that are identical within a nest do not help the model to discriminate between alternatives within the nest. Instead, those variables are pushed to the next upper level of the hierarchy and retained there if they help to discriminate between nests at that level. The probability of choosing alternative i in a two-level nested model is the product of two multinomial logit probabilities in the form of the marginal probability of choosing nest t (sometimes called the upper model), and the probability of choosing i conditional on choosing nest t (for three or more levels of nesting, there is a multinomial logit probability formula for each nest):

$$
P_i = P_{i|t} \cdot P_t = \frac{e^{(Z_i+W_t)/\lambda_t}}{\sum_{j\in B_t} e^{(Z_j+W_t)/\lambda_t}} \cdot \frac{e^{W_t+\lambda_t I_t}}{\sum_{s=1}^{S} e^{W_s+\lambda_s I_s}}
$$

  In the formula above, I_t is the logsum or expected maximum utility of a nest, which is given by:

$$
I_s = \ln\left(\sum_{j\in B_s} e^{Z_j/\lambda_s}\right)
$$

As discussed above, in our probabilistic multinomial model there are no alternative-specific variables (i.e., , and $Z_j = 0$ for all j), and as a consequence all individual-level variables are pushed to the top nest (since they are constant within lower nests). This means that ultimately there is only one "nest" (the top model). Consequently, the logit probability becomes:

$$P_i = P_{i|t} \cdot P_t = 1 \cdot \frac{e^{W_t + \lambda_t ln(1)}}{\sum_{s=1}^{S} e^{W_s + \lambda_s ln(1)}} = \frac{e^{W_t}}{\sum_{s=1}^{S} e^{W_s}}$$

The above is simply the multinomial logit probability that we had before, with each alternative collapsing into its own "nest". This shows that a nested logit model is not a feasible model structure for a situation where alternative-specific variables are not available.

- The authors aggregated the responses to perceptual statements into three categories. Please explain the reasons for doing that and provide a frequency table of responses to these questions considering all categories used in the original instrument. Maybe, the instrument design could be biased, and people answers tend to be concentrated in extreme categories.

  Table 1 reports the frequencies of the categories. Categories were aggregated to avoid having numerous categories with very low frequencies. After doing this there is no evidence that answers tend to be concentrated in extreme categories beyond what is usually seen in other research (e.g., Paez, 2013).

- Please support the reason why keeping parameters in the model that are not significant.

  As discussed above, the individual-level variables are given in reference to one of the states (i.e., modes) in the analysis. We did not retain variables whose coefficients were not significant in any of the latent functions (for instance, gender, as mentioned in response to a question from Reviewer 1); however, if a variable had at least one significant coefficient in any latent function, we kept those coefficients for all functions. The reason for this is somewhat pragmatic, since the software that we use for estimation does not allow us to suppress the coefficients for the same variable in only some latent functions. That said, we believe that including those non-significant coefficients is informative, because they tell us for which states a variable has discriminatory value.

- The authors included perceptual indicators directly in the choice model. The direct inclusion of these indicators imposes some difficulties when using the model for forecasting. Accurate forecast for the responses to specific statements could not be available in future scenarios. Thus, this approach is not recommended in the literature. An integrated choice and latent variable model could overcome this issue and could be a more appropriate framework considering the data available in the study. Indeed, it could provide the opportunity to include some exogenous attributes that could "cause" the latent variables capturing perceptions.

  A latent class model is given by the following probabilities:

$q \backslash i$	1	$\cdots$	i	$\cdots$	J	Right Marginal
1	$P_{1\|1} = p_1 \cdot P_{11}$	$\cdots$	$P_{i\|1} = p_1 \cdot P_{i1}$	$\cdots$	$P_{J\|1} = p_1 \cdot P_{J1}$	p_1
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
q	$P_{1\|q} = p_q \cdot P_{1q}$	$\cdots$	$P_{i\|q} = p_q \cdot P_{iq}$	$\cdots$	$P_{J\|q} = p_q \cdot P_{Jq}$	p_q
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
Q	$P_{1\|Q} = p_Q \cdot P_{1Q}$	$\cdots$	$P_{i\|Q} = p_Q \cdot P_{iQ}$	$\cdots$	$P_{J\|Q} = p_Q \cdot P_{JQ}$	p_Q
–	–	–	–	–	–	–

$q\backslash i$	1	$\cdots$	i	$\cdots$	J	Right Marginal
Bottom Marginal	P_1	$\cdots$	P_i	$\cdots$	P_J	$\sum_q^Q \sum_i^J P_{i\|q} = 1$

In the table above $P_{i|q}$ is the probability of choosing alternative i conditional on being a member of latent class q. The choice probability P_iq has utility functions V_{iq} $(i = 1, \cdots, J)$ that depend on alternative-level variables:

$$P_{iq} = \frac{e^{V_{iq}}}{\sum_k^J e^{V_{kq}}}$$

Next, p_q is the probability of being a member of latent class q $(q = 1, \cdots, Q)$, with γ_q a vector of size $1 \times h$ and x_1 is a vector of h individual-level attributes (and $\gamma_1 = 0 to avoid perfect multicollinearity$):

$$p_q = \frac{e^{\gamma_q' x_i}}{\sum_{z=1}^Q e^{\gamma_z' x_i}}$$

P_i, the bottom marginal in the table, is the unconditional probability of choosing alternative i:

$$P_i = \sum_q^Q P_{i|q} = p_1 \cdot P_{i1} + \cdots + p_q \cdot P_{iq} + \cdots + p_Q \cdot P_{iQ}$$

It is well-known that this P_i is the weighted average of the class probabilities. On the other hand, the right marginal is, by design, the probability of latent class q:

$$p_q = \sum_i^J P_{i|q} = p_q \cdot P_{1|q} + \cdots + p_q \cdot P_{i|q} + \cdots + p_q \cdot P_{J|q}$$

The probabilities satisfy the following property:

$$\sum_q^Q \sum_i^J P_{i|q} = \sum_i^J P_i = \sum_q^Q p_q = 1$$

Turning our attention to the case When there are no alternative-specific variables in the model, it is easy to see that the conditional choice probabilities become:

$$P_{iq} = \frac{e^0}{J \cdot e^0} = \frac{1}{J}$$

which means that the right marginal is:

$$\sum_i^J P_{i|q} = \frac{p_q}{J} + \cdots + \frac{p_q}{J} + \cdots + \frac{p_q}{J} = p_q$$

This shows that since there are no alternative-specific variables, the choice probabilities become uninformative. This is also seen in the right marginals:

$$P_i = \sum_q^Q P_{i|q} = \frac{p_1}{J} + \cdots + \frac{p_q}{J} + \cdots + \frac{p_Q}{J} = \frac{1}{J} \sum_q^Q p_q = \frac{1}{J}$$

Since there is no information about the alternatives, the model cannot discriminate between them. The latent class probabilities, on the other hand, are informative, and since they are set up in such a way that each latent class corresponds a trip being in a certain state (i.e., it is by a certain mode), the model reduces to a the multinomial logit model that we use in this paper - what you might call a pure latent class model.

- Explain the rationale for considering the perception of cycling condition in the neighbourhood in models comparing walking with other modes (different for cycling).

  This comment follows from the assumption that the analysis was based on pairwise analysis of the different modes. As explained above, the structure of the model is multinomial, which is why changes in cycling affect the probabilities of all states.

- Only when perceptions of the walking condition in the neighbourhood are good, walking is preferred from Car/motorcycle, bus, and others. Perceptions of the walking condition in the neighbourhood seem to be not important for bicycle and rickshaw use.

  Since the probabilities all adjust to changes in any one outcome, the perceptions of walking condition in the neighborhood affect bicycle and rickshaw use; however, the effect is relatively small for rickshaw, although more noticeable for bicycle (see Figs. 3 and 4).

- The authors report that perceived security from crime influences auto use. However, it also promotes bicycle and rickshaw use compared to walking . This result seems to be counterintuitive, as other research in Global South countries indicates that higher security promotes walking trips (Arellana et al., 2020; Larrañaga et al., 2016).

  Thanks for this comment. The manuscript was edited to discuss that social conditions in the neighborhood, including higher levels of perceived safety from crime, tend to associate positively with the use of UAT and rickshaw. Also, perceived safety from crime influences auto use. In the Bangladeshi context, auto use is a proxy for higher income. Therefore, it seems possible that auto users tend to live in high income neighborhoods, which are generally perceived as safe.

- Furthermore, signs of the parameters concerning the perception of crime (moderate and good) are the opposite. Please explain why this happens.

  Recall that the parameters are relative to the reference. For this reason, interpretation can become complex, which is why we simulate the probabilities to more easily grasp the effects of changes in these variables (see Figs. 1-4). The simulated probabilities are discussed in the text.

-The conclusion reported in line 824, page 3 3, is not supported by the data analysis. Even though it is expected that perceptions and attitudes can be influenced by developing and designing walking- and cycling-friendly neighbourhoods, the model does not support that the improvement of physical conditions will increase the utility of active travel. Also, besides that, promotional activities could help to improve the perceptions regarding built environment conditions, the study does not support what will the impact be on perceptions if such activities are implemented.

We agree that there is no evidence that improving the conditions of the built environment will result in improved perceptions of the built environment, but it is a reasonable supposition. Then, assuming that that is the case, the analysis supports the following statements:

1. When percepctions of the environment are moderate or good the probabilities of walking and cycling increase; the gains in the probability of cycling are larger for dedicated cyclists, that is, those who cycle more per day. The same is true for perception of the conditions for cycling

2. When perception of crime improves the probability of active travel increases in general; the gains are bigger when conditions for walking are moderate or good, and the effect is also larger for dedicated cyclists, that is, those who cycle more per day.

Furthermore, the authors claim that daily cycling time influences the use of the cycle. However, I am wondering if the causal relation is not the opposite (i.e. the bicycle possession and being cyclist will promote experience longer cycling time every day).

This is an interesting point. We use daily cycling with the purpose of identifying dedicated cyclists; as long as we can discriminate between people who are committed cyclists and others we can at least find differences in the probability of various modes. As the analysis shows, committed cyclists are much more likely to cycle in general, but also their probability to walk for shorter trips remains high.

There is some literature regarding active mode choice and use in the Global South context that is not mentioned in the paper. The sentence indicating that only a few studies are available that focus on the covariates of modes used for transportation in developing countries, particularly concerning UAT , is not entirely accurate. Some references related to this topic are:

Thank you for sharing these references with us. We have cited them in appropriate places in the paper.

Oliva, I., Galilea, P., & Hurtubia, R. (2018). Identifying cycling-inducing neighborhoods: A latent class approach. International journal of sustainable transportation, 12(10), 701-713.

Larranaga, A. M., Rizzi, L. I., Arellana, J., Strambi, O., & Cybis, H. B. B. (2016). The influence of built environment and travel attitudes on walking: A case study of Porto Alegre, Brazil. International Journal of Sustainable Transportation, 10(4), 332–342.

Rossetti, T., Saud, V., & Hurtubia, R. (2017). I want to ride it where I like: Measuring design preferences in cycling infrastructure. Transportation, 1–22.

Guzman, L. A., Arellana, J., & Alvarez, V. (2020). Confronting congestion in urban areas: Developing Sustainable Mobility Plans for public and private organizations in Bogotá. Transportation Research Part A: Policy and Practice, 134, 321-335.

Arellana, J., Saltarín, M., Larrañaga, A. M., Alvarez, V., & Henao, C. A. (2020). Urban walkability considering pedestrians' perceptions of the built environment: a 10-year review and a case study in a medium-sized city in Latin America. Transport reviews, 40(2), 183-203.

Larranaga, A. M., Arellana, J., Rizzi, L. I., Strambi, O., & Cybis, H. B. B. (2019). Using best–worst scaling to identify barriers to walkability: a study of Porto Alegre, Brazil. Transportation, 46(6), 2347-2379.

Rosas-Satizábal, D., & Rodriguez-Valencia, A. (2019). Factors and policies explaining the emergence of the bicycle commuter in Bogotá. Case studies on transport policy, 7(1), 138-149.

Besides the lack of adequate pedestrian and cyclist infrastructure, they mostly perceive that physical conditions of the neighbourhood regarding walking and cycling are good. This is in line with Arellana et al. (2019) that reports some heterogeneity of perceptions when evaluating conditions of infrastructure. They report differences in perceptions based on their past experiences. People used to live in zones with poor infrastructure could be more tolerant than people that live in zones with better infrastructure.

Arellana, J., Fuentes, L., Cantillo, J., & Alvarez, V. (2019). Multivariate analysis of user perceptions about the serviceability of urban roads: case of Barranquilla. International Journal of Pavement Engineering, 1-10.

Finally, there are some typos throughout the document. A careful revision of the language and the manuscript is needed. Also, please check the legends and symbols in the figures. It is quite hard to note the differences when the paper is printed in B&W.

We have proofread the paper to resolve these issues. Finally, we changed the color palette to viridis. This palette scales to provide colour maps that are perceptually uniform in both colour and black-and-white, and they are designed to be perceived by viewers with common forms of colour blindness.