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Choice Modelling With Time-varying Attributes, With an Application to Train Crowding

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ABSTRACT: This study is concerned with the treatment of time-varying attributes (TVAs) in discrete choice models, where the attributes are some measure of the quality of an alternative that changes over some relevant measure of time. Examples include public transport crowding, traffic congestion, and quality of life. Various methods for representing TVAs are considered, including a number of simplified approaches that only use a single measure, a decomposition approach that presents the amount of time spent in different conditions, and more complex representations that account for variability in the TVA outcome. A study of train crowding is used to test these alternative representations. The results indicate that the simplified approaches are problematic and may bias valuations of TVAs, and that the decomposition approach is less susceptible to these problems and allows for greater insight into potential threshold and nonlinear effects.

KEY WORDS: ***Train crowding, time-varying attributes, intra-trip crowding variability, inter-trip crowding variability, discrete choice experiment, value of travel time savings***

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1. Introduction

When estimating discrete choice models, the attributes of the choice alternatives are a key component of most model specifications. Measures of time or duration are common types of attributes investigated by analysts. Examples include travel time in the field of transportation, life expectancy in health economics, and product life in marketing. Other attributes are linked to time, in that they are a measure of the quality or condition of the alternative either at some *point* in time, or for some *length* of time. For example, travel time when driving is sometimes broken down into time in one of several driving conditions, such as free flow, slowed down and stop-start (e.g., Hensher 2001). Essentially, the aggregate time attribute is decomposed, such that it represents the sum of time spent in various conditions. Other possible applications include time in various crowding conditions when travelling by train (the focus of this study), the quality of cycling infrastructure along a route (e.g., Wardman et al. 2007), the deterioration of health over a life expectancy, and the degradation of performance of a phone over the length of its life.

This paper is an investigation of these types of attributes, which we refer to as time-varying attributes (TVAs). A similar concept called common-metric attributes has been suggested in the literature (Layton and Hensher 2010), which refers to attributes that have the same metric and might be processed in certain ways, such as aggregation. However, TVAs are a specific case of common-metrics attributes, and relate explicitly to *time* under certain conditions.

Of relevance is how the time-varying attribute's conditions may change over time. Some TVAs may be inherently discrete in nature, with well-defined conditions in which time can be spent. Consider bicycle infrastructure, which could come in one of a number forms, such as segregated off-road cycleway and segregated on-road cycle lanes. When a cyclist makes a trip, they may experience one or more types of road or bicycle infrastructure, and spend a certain proportion of their total trip time in each (Wardman et al. 2007). Another example of distinct, discrete TVAs is if time on public transport is broken down into time sitting and time in which one must stand. Wardman and Whelan (2011) note that several unpublished studies in the United Kingdom have employed this approach, but also caution that the crowding level may vary across the time spent seated or standing. Public transport crowding is an example of a TVA in which the crowding level may be relatively continuous in nature, in that the crowding level gradually changes over the trip length. A challenge then is to find an appropriate way of representing these continuous TVAs. Boundaries can be imposed, resulting in a discrete number of conditions, with a certain amount of time (potentially zero) spent in each, but the question then is what boundaries should be employed. In the crowding literature, there has been a shift in recent years to the use of many crowding levels (e.g., Whelan and Crockett 2009; Hensher et al. 2011; Li and Hensher 2011, 2013), yet this does not scale well when time in each crowding condition must be processed by survey respondents.

To complicate matters further, there may be a degree of ambiguity about what is changing over time. A car trip may include varying levels of congestion over the length of the trip, but the congestion itself may be perceived as a mix of factors, including but not limited to proximity to other cars, actual speed relative to the speed limit, and speed oscillations. The question then is how best to represent TVAs in stated choice studies, where we wish to gain an empirical understanding of how individuals value the TVA, its various conditions, and associated dynamics. The most common approach with crowding studies is to utilize a single crowding measure (e.g., Whelan and Crockett 2009, Hensher et al. 2011). This measure may be framed as crowding over the entire trip, or crowding at a single snapshot in time. In some cases, the time at or over which the crowding applies is left unspecified. This study will show empirically that these simplified approaches can be very problematic.

In this paper, various ways of representing TVAs will be discussed in detail, with potential advantages and disadvantages identified for each. The handling of risky outcomes with TVAs will also be discussed. Then, we describe a stated choice survey which depicts train crowding in three different ways: as a single measure, as the time in five different crowding conditions, and as three possible outcomes, each described by time in different crowding conditions, and associated with a probability of occurrence. The model results will focus on the problems associated with the simplified presentations, and the improved performance once the trip time is decomposed by crowding level.

2. Alternative approaches for representing and valuing time-varying attributes

In this section, each of the approaches to representing TVAs will be considered in more detail. Examples will mostly be given in the context of train crowding, however some other examples will also be introduced.

First, it is worth noting that a study may be conducted with no decomposition of a time attribute into time in various conditions, with a focus given to the time attribute only. For example, the value of travel time savings (VTTS) could be estimated with no regard to public transport crowding or traffic congestion. A risk with this approach is that there will be a plurity of real life experiences of crowding and traffic congestion, and these experiences may be projected onto a hypothetical choice scenario, in the absence of an explicit treatment of these attributes. One individual may evaluate the time savings in terms of no crowding, while another may evaluate the same time savings in terms of heavy crowding, and so have a higher VTTS. This could have implications for the retrieved VTTS, perhaps manifesting itself as random preference heterogeneity. A more appropriate approach is to make efforts to disentangle the value of time and the value of quality measures related to time, such as crowding and congestion.

One approach to representing TVAs is to take a snapshot as some point in time (see, for example, some of the studies reviewed in Wardman and Whelan 2011). Whilst this is easy for the analyst to implement, and relatively easy for the respondent to process, there is an ambiguity as to how the respondent extrapolates from that snapshot in time to the entire duration. If, for example, crowding was framed in terms of the crowding level at boarding, then the respondent may infer some change in crowding after that time based on their own experiences of changing crowding levels along the length of the trip. It is uncertain then exactly what crowding condition is being valued.

This ambiguity could be overcome by specifying the same condition for the entire duration. Wardman and Whelan (2011) note in a train crowding context that such a specification might not be perceived as credible. Again, a respondent might ‘adjust’ the crowding level to reflect some realistic level of variation over the trip. Whilst this adjustment might seem less likely for the entire-time crowding framing than the snapshot framing, this study will empirically show that respondents do interpret a single crowding level differently, for both the snapshot and the entire-trip framing of the crowding attribute. The disadvantages of a single crowding measure extend beyond framing effects. The entire-time approach is ill suited if the analyst wishes to test for threshold or penalty effects, in which evaluation of the alternative might be disproportionately influenced by even limited time exposure to a particular condition. It would also be a poor environment for testing nonlinear responses to the various conditions.

One way to overcome the ambiguity problem of the snapshot approach and potentially overcome the credibility problem of the entire-time approach is to decompose the total time into time in the various conditions associated with the TVA. For example, train trip time could be decomposed into time sitting, and time standing in various crowd densities. Nonlinear responses can be more effectively captured. Consider an example where we wish to investigate the impact of heavy crowding on a 40 minute train trip. With a single crowding measure, we can only test zero or 40 minutes of heavy crowding. By decomposing the trip time, we could test, say, a 10 minute duration under heavy crowding, in the context of the 40 minute trip, rather than in the context of a 10 minute trip. The decomposition approach also helps identify possible thresholds, which also might vary as a function of total trip time. The downside of this approach is that it places a greater cognitive load on the respondent, and so cognitive and motivational limits might be exceeded.

The analyst may be interested in how individuals respond to risky outcomes in the context of TVAs. The issue here specifically is the variability in the mix of conditions over the length of time, rather than the time variability itself. For example, train passengers may have a reliable train service, but variable levels of crowding, due to random demand fluctuations across the rail network. Since the travel time is not varying in this example, schedule delay (Small 1982) is not the issue. Rather, passengers may place some penalty on alternatives with more variable crowding experiences. This could take the form of a mean-variance model (e.g., Senna 1994), or individuals might impose penalties if certain conditions are *ever* encountered. For example, an older passenger might disproportionately dislike a train service that has a non-negligible probability of requiring them to stand.

If the analyst is to place a value on risky outcomes in the context of TVAs, using stated choice methods, then the choice task is going to be complex. Even with variability of a single travel time measure, there are a variety of ways of presenting the variability (see Li et al. 2010). Yet with TVAs, the attribute becomes a multivariate random variable: the time under *each* of the conditions may vary, rather than just a single measure of time. The evaluation of each outcome will require the evaluation of times for each of the conditions, and so the dimensionality is high. This discourages the use of eqi-probable outcomes (e.g., Senna 1994), which will not be an efficient use of the respondents' attention. In this paper, we present three train experiences per alternative, each with a probability attached, and described by five levels of crowding. However, we will only use the expected values in the present analysis, and reserve a richer investigation of inter-trip crowding variability for future research.

3. Methodology and empirical setting

This paper empirically investigates alternative presentations of TVAs in the context of train crowding. In October 2016, a stated choice study was conducted in the Sydney region, focusing on the Bankstown line (see Figure 1). Survey participants' home station had to be between Carramar and Erskineville, inclusive. This removed the complication of route choice, which is available to some users of stations further out along the line. The Bankstown line has relatively high crowding, with an average load factor between 8am and 9am of 120 percent (Transport for NSW 2014). This load factor, which measures the ratio of boarded passengers to seated capacity, was sampled at Erskineville, which is just prior to the first CBD station, Redfern, which has a substantial number of offloads. Thus, Erskineville is typically the location with the highest crowding level on this line. The Bankstown line is also being considered for conversion to metro along most of the line, which will have implications for the number of number of available seats, and the mix of crowding experiences across the day and along the line. This conversion motivates a more nuanced understanding of passenger valuation of crowding.

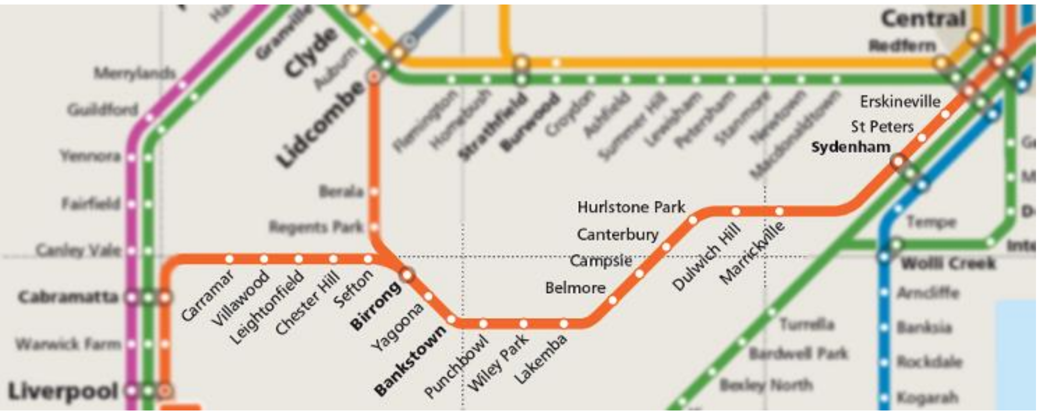

Figure 1: Study area: Bankstown line, Sydney

Survey participants were recruited at one of three shopping centers along the train line, and took part in a computer assisted personal interview that averaged 15 minutes duration. To be eligible for the study, participants had to travel to or from work on the Bankstown line at least once a week. The trip direction had to be towards the Central Business District (CBD) in the morning peak (6am-10am) or away from the CBD in the evening peak (3pm-7pm), thus ensuring that they travel at a time and in a direction with relatively high crowding levels. Two hundred individuals completed the survey. Of these, 30 chose lexicographically with respect to price over all nine choice tasks, and were dropped from the analysis, resulting in 170 respondents and a total of 1530 choice observations.

Prior to the presentation of the choice tasks in the survey, information on a typical eligible train trip was collected. There were then nine choice tasks in total, with each respondent being shown three choice tasks for each of the train crowding presentations examined, where these will be considered in detail below. Two train alternatives were made available for choice. Both forced and unforced choice responses were collected, with the former used in the present analysis. Figure 2 shows an example choice task, with a single crowding measure shown.

The fare attribute levels were drawn from one of three possible sets of levels, depending on the length of their trip. The frequency could be every 5, 10, 15 or 20 minutes. Station crowding was handled by varying the time to enter/exit/transfer through the station closest to the CBD (1, 2 or 3 minutes), and by varying the crowding level as they moved through the station (little, moderate or heavy crowding). Station crowding will not be examined in this paper in detail. Irrespective of the train crowding presentation shown, five possible train crowding levels/conditions were considered. Two of these are associated with sitting. Either the passenger can sit next to a free space or companion, or they must sit next to a stranger, where the latter is potentially more onerous. For both sitting conditions, the individual may opt to stand instead – they merely have the option to sit. There are three standing conditions: little, moderate and heavy, with respondents told the corresponding number of passengers standing in the vestibule (see Figure 3) and shown top-down diagrams of what this might look like. A *d*-efficient design was generated in the Ngene software.

Choose your preferred train service 1/9

Consider the following two potential train services for your travel to work. Both arrive at St James at 08:02.

Choose which train service you prefer.

	Train service 1	**Train service 2**
Fare	$3.90	$4.50
Frequency	Every 15m (minutes)	Every 5m (minutes)
Total time on train	15m	13m
Crowding on train for the entire trip	Seat available, next to a free space or companion or stand with little crowding	Must stand, heavy crowding (21+ passengers standing in the vestibule - image)
Arrival station: St James		
Time to exit station after alighting	3m	1m
Crowding while exiting station (definitions)	Heavy crowding	Moderate crowding
Which train service do you prefer?	○ Train service 1	○ Train service 2
For each train service, if it was your regular service, would you:	○ Use this train service ○ Travel earlier to reduce crowding ○ Travel later to reduce crowding ○ Stop travelling to work by train	○ Use this train service ○ Travel earlier to reduce crowding ○ Travel later to reduce crowding ○ Stop travelling to work by train

Figure 2: Example choice task, with single crowding measure

The first crowding presentation format shown was the single crowding measure, shown in Figure 2. Respondents were randomly allocated to one of two crowding level framings: crowding for the entire trip, and crowding at the time of boarding (i.e., the snapshot approach). Additionally, respondents were randomly allocated to either morning travel towards the CBD, or evening travel away from the CBD. The Sydney rail network is CBD-centric, with crowding levels generally increasing on morning peak inbound trains, and decreasing on evening peak outbound trains. This relatively monotonic change in crowding level in real life may have implications for how respondents will make inferences about changing crowding levels when a single crowding measure is employed, especially under the snapshot approach.

Consider the journey to work, in which crowding levels generally increase over the trip. If an at-boarding crowding measure is employed, the respondent may anticipate the crowding getting worse. In this case, as the respondent processes the total travel time, they would be perceiving some mix of crowding conditions that is worse on average that the level presented, they would place greater disutility on this time, and the VTTS would increase. If they have a seat on boarding, then they keep the seat for the rest of the trip, although the general feeling of crowding may increase, with standing passengers encroaching on their space. At a low to intermediate crowding level, there is scope for the crowding level to deteriorate. At heavy crowding levels, there are capacity limits that will prevent crowding from getting worse.

Consider next the journey from work. Here, the crowding levels in Sydney will generally decrease over the trip, respondents may anticipate this, the average crowding conditions will be less than the at-boarding level presented, and the at-boarding VTTS will be lower than the entire-trip VTTS. These hypotheses will be tested in the Results section.

Total time on train	13m	9m
Crowding on train		
- Must stand, heavy crowding (21+ passengers standing in the vestibule - image)	-	-
- Must stand, moderate crowding (11-20 passengers standing in the vestibule - image)	-	-
- Must stand, little crowding (0-10 passengers standing in the vestibule - image)	-	2m
- Seat available, next to a stranger; or stand with little crowding	-	5m
- Seat available, next to a free space or companion; or stand with little crowding	13m	2m

Figure 3: Presentation of crowding in select choice tasks as decomposition of total time on train

The second crowding presentation format decomposed the total time on train, reporting the time under each of the five crowding conditions, where in many instances these times are allowed to be zero (see Figure 3). One way to consider this is as there being *intra*-trip crowding variability. The third crowding presentation format introduces *inter*-trip crowding variability, by showing three 'crowding experiences', each again decomposed into the time under each crowding condition (see Figure 4). In addition, probabilities are assigned to each of the three crowding experiences. The most crowded experience always has a 1/10 probability, and captures the worst experience that the train service provides on a regular basis.

Total time on train		15m			9m	
Crowding on train						
For these numbers of trips out of 10:	**3/10**	**6/10**	**1/10**	**6/10**	**3/10**	**1/10**
You have these crowding experiences:						
- Must stand, heavy crowding (21+ passengers standing in the vestibule - image)	-	-	-	-	5m	9m
- Must stand, moderate crowding (11-20 passengers standing in the vestibule - image)	-	-	4m	-	4m	-
- Must stand, little crowding (0-10 passengers standing in the vestibule - image)	-	-	4m	-	-	-
- Seat available, next to a stranger; or stand with little crowding	4m	15m	7m	9m	-	-
- Seat available, next to a free space or companion; or stand with little crowding	11m	-	-	-	-	-

Figure 4: Presentation of multiple crowding outcomes in select choice tasks

At this stage, only basic multinomial logit models are employed, with the focus being on the comparison of crowding valuations across single crowding measure framing (entire trip, start of trip), and safety presentation (no crowding variability, intra-trip variability, intra and inter-trip variability). The modelling effort and sophistication will be extended in future research.

4. Results

Table 1 contains the results of the MNL model estimated on the single crowding measure data only (i.e., the first three choice tasks that each respondent completed). Separate train crowding parameters are estimated for each combination of the crowding framing shown (at boarding, for the entire trip), and trip direction (to work, from work). For all combinations, the five crowding levels shown to respondents were collapsed to three crowding levels after a specification search. Respondents did not distinguish between the type of seat available (next to a free space or companion, or next to a stranger), or little/moderate crowding when standing. All estimated parameters are significant and of expected sign.

Table 1: MNL model with single crowding measure

Attribute	Crowding framing	Trip direction	Parameter	t-ratio
Fare			-0.7821	-6.13
Frequency			-0.0701	-6.00
Heavy station crowding (minutes)			-0.1847	-2.84
Time on train in crowding level:				
Seat available	At boarding	To work	-0.1038	-2.86
Must stand, little/moderate crowding	At boarding	To work	-0.1405	-3.72
Must stand, heavy crowding	At boarding	To work	-0.1584	-3.53
Seat available	At boarding	From work	-0.1191	-3.91
Must stand, little/moderate crowding	At boarding	From work	-0.1283	-3.78
Must stand, heavy crowding	At boarding	From work	-0.1611	-4.04
Seat available	For entire trip	To work	-0.0734	-2.14
Must stand, little/moderate crowding	For entire trip	To work	-0.0957	-2.46
Must stand, heavy crowding	For entire trip	To work	-0.1398	-3.10
Seat available	For entire trip	From work	-0.1178	-3.69
Must stand, little/moderate crowding	For entire trip	From work	-0.1529	-4.15
Must stand, heavy crowding	For entire trip	From work	-0.1537	-3.70
Model fit				
LL	-312.95			
N	510			
AIC/N	1.286			
K	15			

Table 2 compares the VTTS per crowding level, across the different experimental conditions. Clearly, for any given crowding level, there are differences based both on crowding framing, and trip direction. Earlier, it was hypothesized that when travelling *to* work, respondents would anticipate worsening crowding, and thus have a higher VTTS for each crowding level when the crowding is framed as being at boarding, instead of the entire trip. The results are consistent with this. For sitting time, the VTTS is $7.96 at boarding, compared to $5.63 for the entire trip – a ratio of 1.41:1. For standing with little/moderate crowding, the ratio is similar at 1.47:1. For heavy crowding, the ratio is smaller at 1.13:1, which as suggested earlier may be because it is hard for the crowding level to deteriorate further as the trip progresses, due to capacity limits.

Table 2: Comparison of VTTS under each crowding level ($AUD per person hour)

Crowding level		At boarding	For entire trip	Boarding/ entire trip
Seat available	**To work**	$7.96	$5.63	1.41
Must stand, little/moderate crowding		$10.78	$7.34	1.47
Must stand, heavy crowding		$12.15	$10.73	1.13
Seat available	**From work**	$9.14	$9.03	1.01
Must stand, little/moderate crowding		$9.85	$11.73	0.84
Must stand, heavy crowding		$12.36	$11.79	1.05

Turning to the VTTS comparisons when the choice task was for trips *from* work, there is less of a difference in VTTS based on the framing of crowding. The difference is negligible when a seat is available, or for standing under heavy crowding. However, for standing with little/moderate crowding, the VTTS estimated under the at-boarding framing is now somewhat lower than the VTTS estimated under entire-trip framing. Here, the respondent may have been anticipating an improvement in crowding as the trip progressed, and have factored this into their perception of the crowding level presented to them.

Based on the present evidence, if crowding must be reduced to a single measure, then it is best for that measure to represent crowding over the entire trip. Nonetheless, we can still see notable differences in valuation of crowding depending on trip direction. Particularly notable is the time sitting, with a VTTS of $9.03 for travel from work, and just $5.63 for travel to work. These differences may be due to a desire to get home more quickly than the trip to work. What these results show is that the introduction of ambiguity in terms of when the presented crowding condition applies can lead to a systematic bias in the valuation of the crowding levels. It also raises questions as to what exactly is being measured when VTTS values are retrieved in a study context that does not explicitly consider related TVAs such as train crowding and traffic congestion. A mix of experiences of these attributes might be contributing to variance in the VTTS measure.

The next models that we estimate utilise the decomposition of the total time on train into time in each of the five crowding conditions. Two types of choice tasks are pooled for these models: those that show a single train trip per alternative, and those that show three train trips per alternative (i.e., those with inter-trip crowding variability). In the latter case, the expected values are used in the model. Consider first Model A, reported in Table 3, in which all attributes are entered linearly into the utility expressions. The total time on train is specified, resulting in a base VTTS of $8.61 per hour. The time standing with both little/moderate and heavy crowding are also entered into the utility expressions, such that the associated parameters must be added to the total time parameter to get an overall sensitivity to these crowding conditions. This results in a VTTS of $10.72 for standing with little/moderate crowding, and $13.58 for standing with heavy crowding. These values are reasonable, and a little higher than the averages of the values from the single crowding measure models. Crucially, interactions were tested between trip direction and all of the time parameters, and were not significant. This suggests that respondents are more likely to take the crowding times shown to them at face value, with the VTTS unimpacted by framing effects and ambiguous measures of crowding.

Table 3: MNL model with multiple crowding times

Attribute	Model A Crowding coded linearly Parameter	t-ratio	VTTS ($/person hr)	Model B Crowding coded non-linearly Parameter	t-ratio
Fare	-0.4854	-8.09		0.0560	-8.51
Frequency	-0.0464	-5.84		0.0079	-5.89
Heavy station crowding (minutes)	-0.1800	-5.52	$22.25	0.0311	-5.53
Total time on train	-0.0697	-5.78	$8.61	0.0095	-6.55
Time must stand, with little/moderate crowding	-0.0171	-1.74	$10.72	0.000037	-2.26
Time must stand, with heavy crowding	-0.0402	-2.11	$13.58	0.00041	-3.03
Model fits					
LL	-624.26			-620.48	
N	1020			1020	
AIC/N	1.236			1.228	
K	6			6	

As discussed earlier, by decomposing travel time by crowding condition, threshold effects and nonlinearities are more readily identified. Model B in Table 3 has thresholds and nonlinear effects specified for the two standing crowding attributes. A specification search was conducted over a number of thresholds and nonlinear specifications. The resulting model has improved model fit over Model A. The little/moderate crowding time attribute was specified with a threshold of four minutes, and a cubic transformation. That is, all times over four minutes are cubed, and all times four minutes and under are specified with a time of 64 (i.e. the threshold value cubed). This implies that quite a strong nonlinear effect is present with respect to standing time. The heavy crowding time attribute was specified with a large 16 minute threshold, and was squared. Perhaps the act of getting into a highly crowded train is what generates much of the disutility, especially for shorter trips.

5. Discussion and Conclusion

This research has shown that use of a simplified measure of crowding can introduce problematic biases, and be limiting in terms of retrieving thresholds and nonlinearities. It has examined some of the future directions contemplated by Wardman and Whelan (2011), including the explicit handling of crowding levels that vary over the trip, and nonlinear responses to time in certain crowding conditions. Their call for an investigation of the probabilistic nature of crowding motivated the inclusion of choice tasks with inter-trip variability in this study, however this analysis will be a part of our future research agenda. This agenda will include the specification of nonlinear models that allow for risk attitude and perceptual conditioning (Hensher et al. 2017). In the Sydney context, where long metro lines are currently being built, the nonlinear effects identified in this study flag potential concerns. If passengers must stand over long distances, then there might be negative implications for patronage.

The warning about simplifying TVAs to a single measure extends to other TVAs beyond crowding. Some of the specific dynamics of crowding have been discussed herein, but other TVAs might have other dynamics that might influence how they are perceived in a stated choice study. These dynamics could relate to how the TVA components typically or realistically change over the length of time, or to the context in which the decision is being made. We suggest careful consideration of these dynamics before any study that includes TVAs is conducted. One aspect of TVAs that warrants specific attention is what boundaries are appropriate for delimiting different TVA conditions. The boundaries that the analyst specifies may not match those perceived by the respondent, or the respondent may even choose in real life without consciously perceiving any boundaries at all. There may be experimental alternatives to the use of discrete conditions with associated times. One approach would be to present a sequence of snapshots along the length of time. This could take the form of a video depicting the changes in the attribute. Another alternative is virtual reality. In the case of crowding, a respondent could see the crowding level change around them station after station. For traffic congestion, a driving simulator could represent changes in congestion (traffic proximity, oscillations etc.) implicitly through the traffic around the participant, rather than explicitly in a stated choice task. Thus, TVAs might motivate the use of emerging choice data collection technologies.

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