IMPACT OF CROWDING ON TRAVEL TIME PERCEPTION:

A VIRTUAL REALITY STUDY

A Thesis

Presented to the Faculty of the Graduate School

of Cornell University

In Partial Fulfillment of the Requirements for the Degree of

Master of Science

by

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December 2019

ABSTRACT

Congestion inside a vehicle and travel time are two important influences on utility of a public transport trip. According to psychology literature, perceived time is a subjective measure of duration, which can be distorted by emotions. On the other hand, crowding can cause negative feelings in travelers. Accordingly, we hypothesize that the negative feelings induced by high passenger density can lengthen the perceived travel duration. We set up a novel behavioral experiment using Virtual Reality (VR) technology to address this hypothesis, by simulating short immersive subway trips with different density of virtual passengers. In a first task, retrospective time judgements were obtained after two consecutive trips. In a second task, prospective trip duration estimate, as well as subjective emotional valence of the trip were acquired after each of 5 trips with different passenger congestion levels. Results of the first task only showed an effect of trip order on estimated times. However, in the more comprehensive second task, as predicted, travel time was estimated significantly longer by an increase in passenger density. Further analysis confirmed that this effect is mediated by the negative feelings induced by crowding. Finally, preferences of participants in a Stated Choice (SC) task were compared with responses in the VR task. Results revealed that individuals who disutilize passenger density more negatively in the SC task, also feel more unpleasantly during higher density VR trips. This confirms the validity of hypothetical SC tasks in reflecting individuals' actual feelings about crowding. This study demonstrates the applicability of VR technology for interdisciplinary research intersecting psychology and transportation. Future

research about the implications of the observed interaction between crowding and perceived travel time, in route choice modeling is encouraged.

BIOGRAPHICAL SKETCH

Saeedeh Sadeghi grew up in Shiraz, Iran. She received her B.S. in Computer Engineering from Shiraz University. She then went on to the University of Tehran where she received her M.S in Artificial Intelligence. During her time at the University of Tehran, she worked on modeling decision making and metacognition in healthy and patient individuals. She started as a graduate student in Systems at Cornell University in 2017, working on the applications of cognitive psychology in transportation behaviors. She is now a PhD student in Developmental Psychology at Cornell.

ACKNOWLEDGMENTS

Thank you to all people who provided support and guidance throughout this project. Thank you to my advisor, Dr. Ricardo Daziano for his help and support during the project. Thank you to Dr. So-Yeon Yoon, for providing scientific and technical support helping with creating the Virtual Reality environment, and providing her lab space for conducting experiments. Thank you to Dr. Adam Anderson for his emotional and scientific support during the project. Thank you to Nicholas Cicero, Isaac Jang, and Prateek Bansal for the help they provided for recruitment, testing and design of the experiment. Thank you to the people who participated in this research. This project would not have been possible without the help of all these people.

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CHAPTER 1

INTRODUCTION

In addition to being a major externality, crowding in public transport is becoming an increasingly noteworthy influence on users' modal and route choice along with the more traditionally recognized factors of travel time and cost (Tirachini, Hensher, & Rose, 2013; Wardman & Whelan, 2011). Higher travel time and overcrowding are both unpreferred aspects of a commuting trip. Whereas travel time and congestion inside a vehicle are usually assumed to be independent from each other, an interdisciplinary view of the psychology and transportation literature suggests that subjective perceptions of travel time may in fact be influenced by crowding levels. In this study, we use immersive Virtual Reality (VR) technology to examine the idea that crowding can lengthen perception of travel time.

Background

When an individual subjectively experiences a time interval, the perceived duration is not necessarily equal to the objective duration of the interval. In fact, a large body of literature in psychology studies the mechanisms of time perception and factors that distort one's perception of duration (Block & Grondin, 2014; Grondin, 2010). Emotion and arousal are among these factors, with abundant evidence indicating that both can distort perception of time (Droit-Volet, 2013). For instance, people systematically overestimate the duration of time looking at emotional faces compared

to neutral faces (Droit-Volet, Brunot, & Niedenthal, 2004; Droit-Volet & Meck, 2007). In one experiment, individuals judged perceived duration of 5 seconds standing on a moving cart that either approached a stairwell (danger condition), or moved away from it (no danger condition). It turned out that people perceived time to be longer when in danger conditions (Langer, Wapner, & Werner, 1961). In general, it is widely accepted that high arousal emotional stimuli with negative valence is perceived to be longer in duration than neutral stimuli (Droit-Volet, 2013).

Crowding is a negatively valenced and arousing characteristic of a trip on public transit. Previous studies show that passenger crowding can lead to transit-users' negative affect causing a feeling of stress and discomfort (Cheng, 2010; Cox, Houdmont, & Griffiths, 2006; Kalb & Keating, 1981; Stokols, 1972). Mohd Mahudin and colleagues found various factors contributing to affective reactions to crowding including feeling uncomfortable, distracted, frustrated, stressed, and irritated. The ambient environment in crowded conditions was evaluated as stuffy, smelly, noisy, and hot. Also higher levels of exhaustion and stress due to the experience of crowding was associated with somatic symptoms such as headache, tension, and stiff muscles (N. D. M. Mahudin, Cox, & Griffiths, 2012; N. M. Mahudin, Cox, & Griffiths, 2011). Based on this evidence, we hypothesize that higher passenger density increases the perceived travel duration, by inducing negative affective states.

Related works and research gap

Discrepancy between objective travel time and subjectively reported travel duration

has been observed in a number of previous studies in the transportation literature (Carrion & Levinson, 2019; Delclòs-Alió, Marquet, & Miralles-Guasch, 2017; González, Martínez-Budría, Díaz-Hernández, & Esquivel, 2015; Parthasarathi, Levinson, & Hochmair, 2013; Peer, Knockaert, Koster, & Verhoef, 2014; Tenenboim & Shiftan, 2018; Vreeswijk, Thomas, Van Berkum, & Van Arem, 2014). Obtaining both the objective and subjective travel time in real-world commuting trips is not without methodological complications. Actual travel times have been collected by GPS tracking technology in several studies (e.g. Delclòs-Alió et al. (2017); Parthasarathi et al. (2013)), or from other sources of travel time information between known locations in a number of other studies (e.g. González et al. (2015); Tenenboim & Shiftan (2018)). Travel times were then compared with individuals' reported estimates of trip duration in order to explore discrepancies between the two numbers. Whereas these studies can be useful in finding the difference between the reported and true travel time, it is questionable whether the reported time is in fact equivalent to the perceived time. Peer et al. (2014) concluded a divergence between reported estimate and perceived travel time, finding no relationship between individuals' route choices and the reported times. They suggest several possible reasons for this divergence, including underestimating one's speed due to its social desirability, or overestimating trip duration as a complaint to policy makers. Furthermore, reported travel times are not reliable measures of time perception in most real-world situations, since people sometimes check the time with their personal phone or watch while traveling. Therefore, the reported travel time would not be purely subjective but confounded by

access to objective time. In this study, we aim to set up an experimental paradigm that overcomes these methodological limitations of obtaining travel time perception.

Everyday commuting trips are also not ideal for identifying sources of travel time misperception; because it is difficult – if not impossible – to isolate different potential factors as they interact with each other. For instance, crowding, purpose of the trip, and flexibility of arrival time are usually dependent on each other: Congestion occurs on weekday mornings when many people commute to the workplace, attempting not to be late. Therefore, in this context, it is challenging to distinguish different sources of distortions in time perception. Carrion & Levinson (2019) recently examined several factors that can contribute to travel time perception error of daily work trips. They reanalyzed a dataset that included GPS-based actual travel times, as well as survey-based estimates of participants' usual travel durations. Among the various factors included in their model, higher values of congestion and stress predicted an underestimation of travel time, rather than an overestimation, a finding that contradicted their hypothesis. They associated this observation to participants' not accurately understanding experimenters' intentions by the words 'congestion' and 'stress'. Another source of this conflicting result could be the various interacting explanatory factors included in one model that can lead to unreliable results, such as arrival flexibility, type of trip, congestion level and stress which are all tightly correlated.

Delclòs-Alió et al. (2017) found that university members commuting to/from campus, overestimate travel times more during rush hours. It is not clear which underlying aspects of rush hour account for changes in time perception in their study. Rush hours usually pertain to high density of travelers, stress, travel time unreliability, arrival inflexibility, higher waiting times, or higher likelihood of standing during the trip. any of these factors may or may not be responsible for distortion of time perception.

Present research

Progress in VR technology in recent years has made it possible to simulate highly realistic virtual environments for behavioral research. Here we set up a VR environment to examine the precise effect of passenger density on travel time perception, controlling for other confounding factors in studies of the real world trips. While participants were physically in the lab, they experienced short immersive trips in the VR environment of a subway car with specific density of virtual passengers sitting or standing along with the participant. This paradigm enabled us to examine the impact of passenger density on time perception, controlling for numerous other real-world confounds.

The VR experiment consisted of two tasks to span two different time estimation paradigms. Psychologists categorize time estimation paradigms into prospective and retrospective subgroups (Zakay & Block, 2004). In prospective tasks, individuals have prior knowledge that they are going to judge time intervals. Conversely, in

retrospective paradigms, they are not aware of the time estimation question until after the given activity, when they are asked to judge a past time interval. These two task paradigms involve different types of cognitive processing. A key component of prospective timing is attentiveness to time, while retrospective perception mainly engages memory processes to recall encoded information regarding the interval (Grondin, 2008). In our current experiment, in the first task participants were asked to estimate the duration of two VR trips with high and low passenger density after experiencing both of them. This task was retrospective since it was the first time that participants encountered the time estimation question. The second task consisted of 5 trips with varying passenger density levels. An estimate of perceived travel time, as well as subjective emotional valence of the trip was asked following each trip. Participants knew that trip duration is a focus of interest in this task, making it a prospective paradigm. Heart rate data was recorded during the experiment using a wristband device. Heart rate can be used as an objective measure of physiological arousal needless of subjective report. The purpose of heart rate recording was mainly to explore whether physiological arousal can predict travel time perception or feeling about the trip.

Finally, it is interesting to inspect whether an individual's feeling about VR trips with different passenger density levels, or the time misperception associated to trips is any related to one's decisions in the hypothetical trip choice situations. Accordingly, we included a Stated Preferences (SP) task in the experimental procedure that consisted of

choice situations with alternative attributes of travel time and passenger density. We used discrete choice modeling techniques to extract individual attribute preferences in choosing trips. Comparing results of the SC task with behavioral results enabled us to validate whether heterogeneity in SC preferences can be explained by impressions about crowding in the VR setting.

CHAPTER 2

METHODS

Participants

A number of forty-two individuals were recruited at the Ithaca campus of Cornell University to participate in the experiment. Student volunteers received extra course credit as compensation for their participation. One participant didn't finish the experiment due to feeling nauseous. All other individuals were included in further analysis (N=41). Participants were aged between 19 and 51 years of age (M=22.6, sd=5.5), and consisted of 19 females. All participants gave informed consent in accordance with the Institutional Review Board at Cornell University.

2.2 Virtual Reality (VR) environment

The VR environment was developed to simulate the inside of a subway car, including moving avatars of passengers. The dimensions and the interior of the subway car were created to represent the New York City subway car R160 model (13.61m × 2.59m, 35.25m2) currently on service. Five conditions were used in the experiment to show five different levels of passenger density.

The number of passengers in the car in each condition was determined to have one, two, three, four, and five passengers per square meter. For example, the lowest density condition was created with one passenger per square meter, i.e., 35 passengers in 35 m2, and the highest density condition was with five passengers per square meter, i.e.,

175 in 35m2. Seating and standing passengers were placed with random distributions to look natural while keeping the total number in the car in the incremental ratios.

The 3D computer model of the environment was created in Autodesk 3DS Max, then converted into Twinmotion software where real-time interaction and avatars were added. Interactions allowed a viewer to walk in the subway car and look around the environment and passenger avatars. The avatars were animated to simulate naturalistic behaviors of passengers such as occasionally changing postures, looking at phones, and reading books or magazines.

To experience the virtual environment, we used the HTC VIVE Virtual Reality system with the VR headset (www.vive.com). VIVE display has a resolution of 2,160 × 1,200 (1,080 × 1,200 per eye), 90 Hz refresh rate, and 110 degrees field of view. The experiment was run in the Twinmotion 2018 standalone player on a lab workstation capable of running 3D graphics with an NVIDIA GTX 1070 graphics card.

Table 1 presents the top view of each condition with a screenshot of an eye-level camera view.

Table 1. Details of the five VR conditions

Density level	Density (passengers/wagon)	Participant view screenshot	Cross section view
1	35		
2	70		
3	105		
4	140		

5	175		

Tasks and procedures

The experiment included a number of virtual trips on a subway car. For all trips, the participant first wore the VR headset with the help of the experimenter, and found herself immersed in the VR subway-car environment. Trips started with the recorded standard NYC subway announcement saying “stand clear of the closing doors please”, followed by a bell ringing. Participants then heard the noise of a crowd as they were in the VR environment for the duration of the trip. The trip ended with another bell-ringing sound followed by silence of the crowd noise. All trips were similar, except in the duration and the density of the virtual crowd on the subway car (5 density levels). Duration of the trip was defined as the time between the first bell and the second bell-ringing sounds.

Upon arrival to the lab and signing the consent form, participants were given oral description of a trip and experienced a demo trip. The purpose of the demo trip was to familiarize individuals with the environment and the concept of a virtual trip. The demo trip had a duration of 60 seconds under medium passenger density (level 3).

The remaining of the experiment included two behavioral tasks as well as a discrete choice experiment survey. All questions and surveys were computerized and

implemented using the Qualtrics online platform.

Behavioral tasks

There were two behavioral tasks involving the VR environment. In task 1 participants experienced two consecutive virtual trips, and then were asked questions about the duration of the trips. During the experience of trips, participants were not aware that they would be asked questions about time. Therefore, it can be considered as a retrospective time perception paradigm. In the second task (task 2), participants experienced all 5 density levels in 5 trips. By the time task 2 started, they had become aware that they were going to be asked questions about time, and therefore this task can be associated with prospective time perception. The details of each task are explained below.

Task 1: This task started with experiencing two consecutive virtual trips. Both trips had the same duration of 100 seconds. One trip had the minimum passenger density level (level 1), and the other had the maximum level (level 5). After experiencing the first trip, participants were informed that they will not see the subway environment for a few seconds. Then the experimenter switched the environment, and they observed the subway environment again with the new passenger density level. The order of trips was counterbalanced across participants. After the second trip, participants took off the headset and answered the following three questions on a computer screen:

1) You just experienced two trips. Which trip do you think took a longer time?

2) Estimate duration of the first trip in seconds.

3) Estimate duration of the second trip in seconds.

Task 2: Following task 1, the second task started. Task 2 included experiencing 5 trips with all 5 different passenger density levels in a randomized order, each having a random duration among 60, 70, or 80 seconds (with equal probability). After each trip, participants were asked to take off the headset, and sit on a computer to answer questions about their experience. These questions included the following:

1) Indicate how pleasant you felt during the virtual trip experience you just had, by a number between 1 and 7.

2) Indicate how unpleasant you felt during the virtual trip experience you just had, by a number between 1 and 7.

3) How long was the trip you just experienced? Type your estimate in seconds.

Pleasantness and unpleasantness were asked in two unipolar scales (questions 1 and 2), since the previous research supports it as a more efficient method for obtaining valence and arousal levels, compared to a single bipolar rating scale (Kron, Goldstein, Lee, Gardhouse, & Anderson, 2013; Kron, Pilkiw, Banaei, Goldstein, & Anderson, 2015). In this notion, net emotional valence has been defined as pleasantness rating (question 1) minus unpleasantness rating (question 2). Also arousal, i.e. the overall intensity of one's affective state, has been estimated by adding pleasantness and unpleasantness ratings (Kron et al., 2013)

Stated Choice (SC) task

Design: A SC survey with 6 choice scenarios was included in the experiment. The survey was either answered before or after the VR tasks, with the order determined randomly. Each SC question asked one's preferred choice among two presented subway travel conditions. Each alternative had two attributes: passenger density level, and travel time. In order to minimize heterogeneity of responses due to individuals' assumptions about the trip, participants were primed with a storyline about the trip prior to the SC task. The storyline was as follows:

"*Imagine you are a tourist visiting New York City (NYC). You are going to use subway to visit one of NYC landmarks. In each scenario you will see two transportation options that differ in travel time and crowding level. You need to choose the option you would prefer, among the two available options.*"

Figure 1 shows a sample choice situation of the SC survey. Passenger density had four possible attribute levels illustrated by a bird's eye view diagram of inside a subway car. Density level diagrams were similar to the ones used in a previous study (density levels 3-6 in Tirachini, Hurtubia, Dekker, & Daziano (2017)). The four levels corresponded to 1,2, 4, or 6 standees per square meter, respectively. All seats were occupied in all density levels leaving out the possibility of sitting during the trip, independent of one's chosen alternative. Travel time of each alternative was presented by the number of minutes the trip would take. There were four travel time levels: 15, 17, 22, and 25 minutes. A total number of 24 SC choice situations, grouped in four blocks of 6 questions, was designed. Ngene software was used to find a D-efficient design of the survey (D-error=0.0092) (Metrics, 2012).

Analysis: Following the literature on modeling crowding valuation in transportation science, passengers are considered as random utility maximizers (Tirachini et al., 2013; Wardman & Whelan, 2011). The conditional indirect utility (u) of alternative i for individual n, in choice situation t can be defined as:

$$u_{int} = \beta_{TT,n}\, TT_{int} + \beta_{TTdens,n}\, dens_{int} \times TT_{int} + \varepsilon_{int}$$

where TT is travel time and dens is passenger density. The error terms ε_{int} are assumed to be independent and identically distributed with an extreme value type-1 distribution, such that logit family of models can be estimated (McFadden, 1973). $\beta_{TT,n}$, and $\beta_{TTdens,n}$ are preference parameters for individual n. Heterogeneity of preference parameters across individuals is taken into account, allowing for random taste variation assuming a normal distribution for both parameters. The mixed logit model was fitted to the data using the gmnl package in R (Sarrias & Daziano, 2017).

Note that in the utility function, density is multiplied by travel time to account for the accumulative disutility of being in a crowded vehicle over time. The correlation between individual fitted coefficient estimate of this term ($\beta_{TTdens,n}$) and behavioral results of crowding impressions in the VR task were further examined.

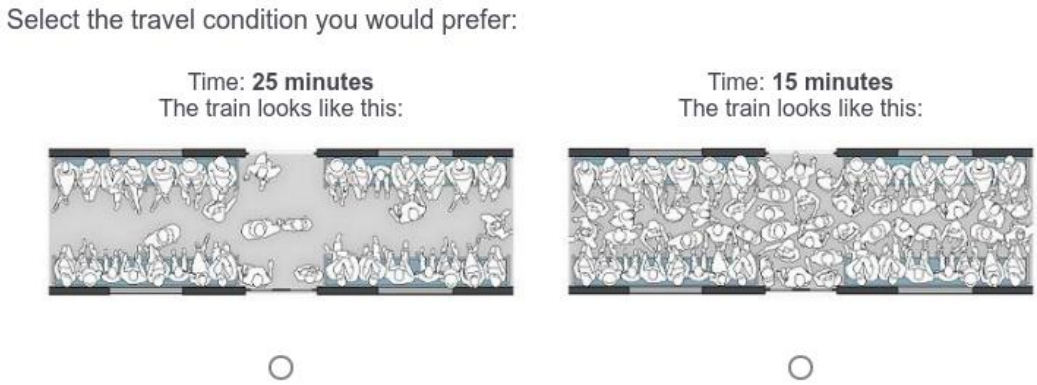

Figure 1. Screenshot of a sample choice scenario of the SC survey

Crowding multiplier is a factor that reflects the disutility of traveling under crowded conditions compared to uncrowded conditions (Tirachini et al., 2013; Wardman & Whelan, 2011). Accordingly, in the above model, Crowding Multiplier (CM) for an individual n and crowding (density) level dens, can be formally defined as:

$$CM_n = \frac{\beta_{TT,n} + \beta_{TTdens,n} \times dens}{\beta_{TT,n}} = 1 + \lambda_n \times dens\,.$$

Where $\lambda_n = \frac{\beta_{TTdens,n}}{\beta_{TT,n}}$. Since λ_n is the ratio of two normally distributed parameters, it has a distribution without moments, making it impossible to analytically obtain parameters such as mean and standard deviation. Therefore, the value of λ_n was estimated for each individual n through simulation, by 1) drawing from the $\beta_{TTdens,n}$, nand $\beta_{TT,n}$ normal distributions (mean and standard deviation taken from model fitting results); 2) estimating a crowding multiplier for the drawn sample; and 3) repeating 1 and 2 for N=1000 times and averaging the results.

Physiological recording and analysis

Cardiac data were recorded during the experiment using the Empatica E4 wristband. E4 is a wireless bluetooth wearable device that detects pulse using Photoplethysmogram (PPG). Interbeat intervals (or RR intervals) are the duration of the interval between two consecutive heartbeats (Note that the instantaneous heart rate is the inverse of RR intervals). RR intervals recorded during each trip were extracted based on the logged start and end time of the trip. Average RR interval for each trip (i.e. inverse of heart rate), was then estimated as an inverse measure of autonomic cardiac arousal during the trip.

CHAPTER 3

RESULTS

Behavioral results of task 1

Although trips were ordered randomly, participants had a bias to identify the first trip as longer: 70.7% of participants selected the first trip as the longest. The higher density trip was selected as the longest by only 53.7% of the participants. As a result, the recency effect seems to be stronger than any potential effect of crowding on time perception that was hypothesized.

Participants were also asked to estimate the duration of each trip in seconds. Results did not show any significant effect of density level on the estimated time (mean estimate for low density condition= 96.6s, mean estimate for high density condition= 102.9s; paired t-test, $t(40)=-1.17$, $p= 0.27$). However, there was again a significant order effect, with the first trip being estimated to be longer than the second trip (mean estimate for first trip= 106.7s, mean estimate for second trip= 92.7s; paired t-test, $t(40)=2.63$, $p= 0.012$)

Behavioral results of task 2

Density of Individuals and Feeling: A higher density of individuals in a public vehicle is usually associated with negative feelings about the trip. Net emotional valence of a trip defined as its pleasantness rating minus its unpleasantness rating is represented in Figure 2.A, averaged for each density level across participants. As we can see, mean valence decreases, as density increases. This was further tested with a

mixed effect linear model predicting emotional valence as a function of the density level, considering the intercept as a random effect that accounts for individual differences (Appendix table A.1). As expected, the results revealed a remarkably significant relationship, with higher density predicting more negative emotional valence (estimate coefficient of density=-1.03, t=-10.48, p=2e-16).

Arousal level, estimated by summing up the pleasantness and unpleasantness ratings was not significantly predictable from density (Appendix table A.2; estimated coefficient of density=2.4e-3, t=0.07, p=0.94). Therefore, higher density has only led to having more negative affect (lower valence), but not to having overall more intense feelings (or arousal).

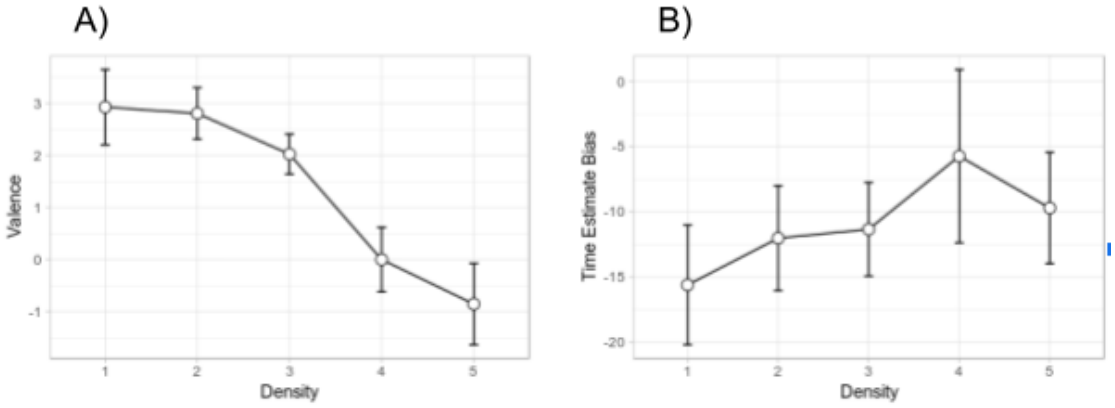

Figure 2. Mean valence and time estimation bias for each crowding level. Error bars represent within-participant standard errors estimated using the method outlined in (Morey, 2008)

Time Perception Bias and density of individuals: In the remaining analysis, time

perception bias (or time estimation bias) is defined as a participant's estimated duration of a trip minus the actual duration of the trip. Figure 2.B represents mean bias in time estimation for each density level. It can be visually noted that there is an ascending trend in time perception bias as density increases. To test this proposition, a mixed effects linear regression analysis was used, predicting bias in perception of time as a function of passenger density (Appendix table A.3). The intercept was treated as a random effect to account for the fact that time estimates of the same individual are more similar to each other than to estimates of another individual. Results revealed a significant effect of density on time perception bias. As hypothesized, higher density was related to a bias towards perceiving the trip as longer (estimated coefficient of density=1.81, t=2.43, p=0.016).

Time Perception Bias and Feeling: Next, we asked if one's bias in estimating the duration of the trip as being longer or shorter is related to the individual's feelings about the trip. A mixed effects linear model with a random individual intercept and a fixed coefficient for valence was used to predict time perception bias as a function of valence (Appendix table A.4). Results revealed a significant effect of valence in predicting time perception bias, with more unpleasant trips being perceived to be longer (estimate coefficient of valence=-1.60, t=-3.67, p=0.0003).

Emotional valence mediates Time perception bias-density relationship: Thus far it has been shown that both density and subjective emotional valence of a trip can

predict the extent to which individuals are biased in estimating the duration of the trip. A further question that is addressed in this section is whether an individual's feeling during the trip, i.e. valence, mediates the relationship between density and time perception bias. Figure 3 represents standardized coefficients of the mixed-effect regressions fitted for the mediation analysis. As we can see, density can significantly predict valence (beta=-0.52, $p<0.001$), and valence can significantly predict time perception bias when density is controlled for (beta= -0.12, $p<0.01$). However, and interestingly, whereas density can independently predict time perception bias (beta=0.07, $p<0.05$), density is no longer a significant predictor if valence is included in the model (beta=0.01, $p>0.05$). Therefore, valence mediates the relationship between time perception bias and density. The mediation package in R (Tingley, Yamamoto, Hirose, Keele, & Imai, 2014) was used to further estimate the direct/indirect effects of density on time perception bias in this mediation analysis. As expected, results revealed a significant mediation effect of valence (estimate=1.65, CI=[0.61, 2.68], p=2e-16), whereas the direct effect of density was non-significant (p=0.88). In sum, results show that passenger density influences perception of travel time not directly, but only through the negative emotional feeling it induces to participants. In other words, the origin of time perception bias is not the crowded environment, but is the more negative feelings that are experienced when being in the crowd.

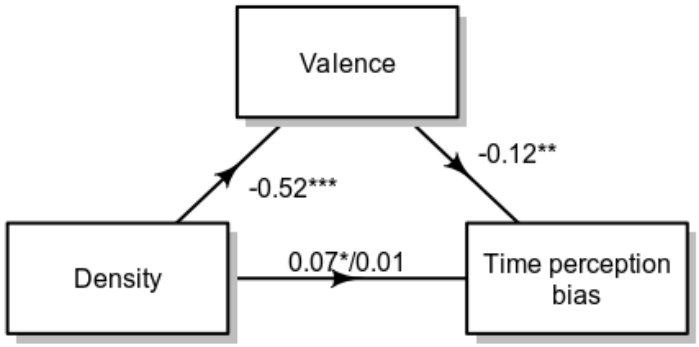

Figure 3. Influence of density on time perception bias, direct or mediated by valence. Numbers represent standardized regression coefficients. The second number on the density-time perception path is the effect when valence is controlled. (* p<0.5, ** p<0.01, *** p<0.001)

Discrete Choice Experiment

All participants finished the discrete choice experiment indicating their preference in 6 discrete choice scenarios assigned to them. Table 2 shows the results of fitting a mixed logit model to participants' responses, allowing random taste variation for the preference parameters of travel time ($\beta_{TT,n}$), and travel time-density level interaction ($\beta_{TTdens,n}$). Expectedly, both $\beta_{TT,n}$ and $\beta_{TTdens,n}$ have significant negative mean estimates.

The crowding multiplier was further estimated for each individual through simulation. Figure 4 represents the mean crowding multiplier for different density levels. As shown in the figure, traveling under the highest density level (level 5) can create a disutility higher than 1.75 times, whereas the lowest density level has on average only

about 1.1 times change in trip utility (compared to a hypothetical level 0 density).

Table 2. Results of the mixed logit model fitted to discrete choice responses. Numbers in parentheses are standard error of the estimate

parameter	mean	standard deviation	Z-value (for mean)
β_{TT}	-0.325 (0.076)	0.305 (0.078)	-4.288 ***
β_{TTdens}	-0.058 (0.01)	0.023 (0.009)	-5.621 ***

*Note: * p<0.05, ** p<0.01, *** p<0.001*

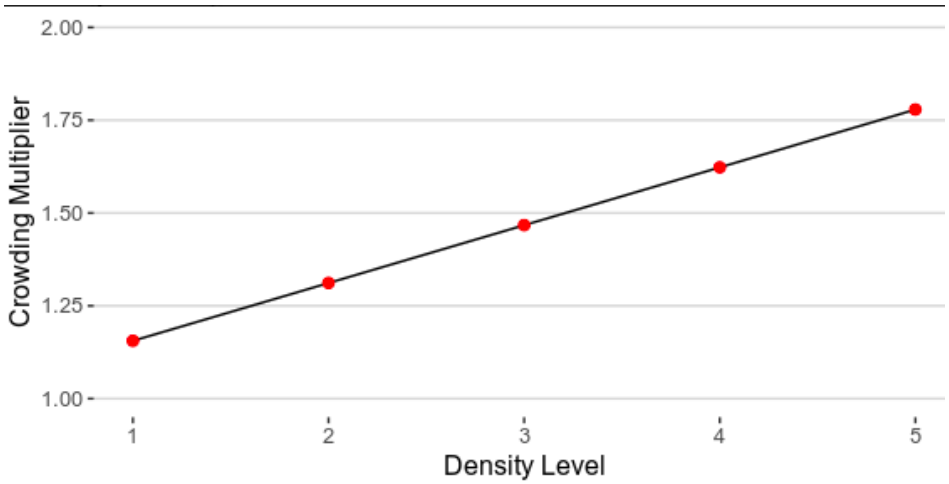

Figure 4. Average simulated crowding multiplier for the 5 density levels

We further examined weather conditional estimates of $\beta_{TTdens,n}$ at the individual level are associated with valence or time estimation bias in the VR task. In order to do this we derived an index of the extent to which passenger density level influences one's bias in perception of time in the VR behavioral task 2. A simple regression was

fitted to each individual's responses in the VR task, with time perception bias as the independent variable, and the density level as the explanatory variable, while also including an intercept. Therefore, the regression for each person had two parameters (slope and intercept) which were estimated from 5 data points corresponding to the trials of the VR task 2. The estimated coefficient of density for each participant, here referred to as time-density-index was considered as an index of how much the person's misperception of time changes, due to one level increase in density. The correlation between time-density-index and the individuals' estimate of $\beta_{TTdens,n}$ obtained from the mixed logit results was then estimated. Results, however, did not show any significant correlation (Pearson's correlation, r=-0.24, p=0.13).

The same process was repeated for valence instead of time perception bias, defining valence-density-index estimated by a simple regression, predicting valence from density level in VR task 2. The estimated coefficient of density in this model, or the valence-density-index represents how much one level increase in density changes valence of the trip for the individual. Interestingly, the correlation between $\beta_{TTdens,n}$ and valence-density-index turned out significant (Pearson's correlation, r=0.45, t(39)=3.15, p=0.0.003), revealing a relationship between heterogeneity of preferences in the discrete choice experiment with the individual's feeling about a trip in the simulated environment. Figure 5 represents the scatterplot of this relationship.

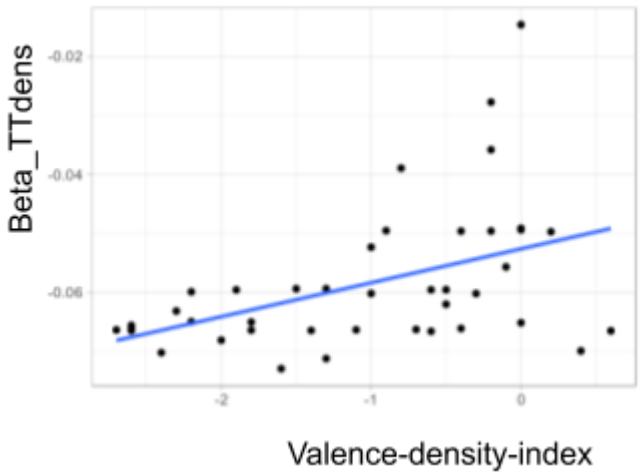

Figure 5. Relationship between valence-density-index (estimated from individuals' indicated pleasantness/unpleasantness ratings in the VR task 2) and estimated $\beta_{TTdens,n}$, n (estimated from the mixed logit model fitted to the DCE responses).

Analysis of cardiac data

The relationship between average RR during a trip and perceived travel duration, or subjective error in perception of time was examined using mixed effects linear regression models. The models were set to predict perceived travel time, or travel time perception error, as a function of average RR with a random effect individual-specific intercept. None of the results were significant (Appendix tables A.5 and A.6). Similarly, average heart rate during the trip was not a significant predictor of the valence or arousal ratings of the trip (Appendix tables A.7 and A.8).

CHAPTER 4

DISCUSSION

Summary of findings

This study explored how density of passengers inside a vehicle can distort perception of travel time in a virtual subway environment.

In the first task, participants retrospectively estimated duration of two consecutive trips, whereas the trips were both equally long unbeknownst to them. Results did not show any significant effect of passenger density on time perception, but an effect of trip order was observed: the first trip was systematically estimated as longer. This is a known effect in retrospective time perception judgments, referred to as the time-order effect (Block, 1985). According to this notion, the first experience of the two is accompanied by higher contextual changes from the participant's point of view, and therefore is encoded in memory as longer. This explanation is especially relevant to our task, since most participants had little or no prior experience with VR technology. Although they first experienced a short demo trip at the beginning before the main tasks to become familiar with the VR environment, it is likely that the first trip in the first task was still perceived as more salient and novel than the second trip in this task.

The most important procedure of the experiment was the second task in which participants experienced five different passenger density levels in five trips.

Participants stated the emotional valence of the trip and the perceived duration following each experience. Three major findings can be inferred from the results, namely:

1) As expected, trips with higher passenger density were rated as more negatively valenced. This finding validates that virtual avatars in the VR environment were sufficiently realistic to induce those negative feelings associated with overcrowding.

2) Most importantly, our main hypothesis was confirmed that passenger density can influence perception of travel time duration. Higher density of passengers did significantly increase estimated duration of the trips. Therefore, retrospective time perception, i.e. estimating duration of a trip with prior knowledge that time intervals must be judged, is impacted by passengers' density. Although this effect was not significant in the first task, i.e. the retrospective task, as mentioned before, the reason could possibly be due to the confound of task order effect. Furthermore, in the second task, each participant experienced a higher number of trips (5 trips), compared to the first task (2 trips), making the second task more statistically powerful and reliable.

3) The effect of passenger density on time perception error was mediated by emotional valence of the trip. Higher density of individuals induced negative feelings, and it was through these feelings that travel time was perceived longer. This is aligned with our hypothesis and rules out other potential explanations for the relationship between passenger density and time perception. Accordingly, the more emotionally susceptible an individual is to the density of people inside a vehicle, his or her perception of time is more affected by overcrowding.

Moreover, one's impression of crowding in VR experiences was compared with preferences in hypothetical choice situations in an SC task. On the one hand, individuals who disutilized passenger density more negatively in the SC task, also felt more unpleasantly during higher density VR trips. Therefore, heterogeneity of responses in the SC task can partly be associated with individual differences in feeling unpleasant in a crowded vehicle. This confirms the capability of SC surveys in reflecting actual preferences and feelings about density in a vehicle.

On the other hand, participants' time density indices, a measure of travel time estimate error's affectedness by density were not correlated with preferences in the SC task. This finding indicates that the extent to which a person disutilizes passenger density in hypothetical choice situations is not related to the amount their perception of time varies due to density. A likely explanation is that the human mind does not have an actual clue of the amount of time perception error (otherwise the error would have been zero); therefore, this error can only be captured in an actual experience of a trip but not a hypothetical choice situation.

Heart rate analysis during the VR trips showed no effect of heart rate on time perception or subjective ratings of valence. In general, indicators of higher physiological arousal, such as increase in heart rate, are associated with a lengthened perception of time (Mella, Conty, & Pouthas, 2011; Treisman, Faulkner, Naish, &

Brogan, 1990). However, most previous efforts seeking to find a direct relationship between time perception and heart rate, independent of stimulus content, have been unsuccessful (Dormal, Heeren, Pesenti, & Maurage, 2018; Schwarz, Winkler, & Sedlmeier, 2013; Suárez-Pinilla, Nikiforou, Fountas, Seth, & Roseboom, 2018). Similar to these studies, here we did not find such a direct relationship either.

Limitations

The duration of a subway trip in the current study was significantly shorter than a real-world commuting trip. Each participant had to experience a total of 7 trips (2 trips in the first task and 5 in the second task) during the experimental session. Thus, the experiment would have been excessively long, had the trips' duration been realistic. It is probable that time perception error or pleasantness of a trip be different if the trip duration increases and gets closer to real trips.

Furthermore, virtual experience with the current VR technology, despite being highly realistic, is not exactly similar to a real experience. Participants knew that virtual avatars were not real humans. They also didn't actually intend to travel to a destination, and were only asked to imagine so. These differences with real travel experiences can possibly impact perception of time or pleasantness feelings to be different from a real experience.

Another limitation of this study is that participants were mostly university students

with a young average age. Accordingly, demographics of our sample of participants is probably significantly different from the population of subway travelers. The effect of demographics such as age, or occupation on pleasantness of different density trips or time perception requires further investigation.

All in all, the trips being virtual, their short duration, and specific demographics of our participants are the limitations of the current study, which could possibly impact the results. Accordingly, here we only compared responses in different density conditions, and avoided inferring about the absolute value of time perception error, or pleasantness ratings in one condition. Although our results showed a significant effect of density on perception of time, the magnitude of this effect can be larger or smaller in the real world.

Future directions

Investigating theoretical choice modeling approaches is beyond the scope of the current experimental study. Nevertheless, the implications of our findings in choice modeling is an interesting avenue for future research. Several previous scholars have proposed using perceived travel time instead of the objective travel time in order to improve choice models (Clark, 1982; Varotto, Glerum, Stathopoulos, Bierlaire, & Longo, 2017; Yáñez, Raveau, & Ortúzar, 2010). Here we found an interaction between passenger density and travel time perception. If and how passenger density could be included in such models along with perceived travel time requires further

investigation.

Finally, progress in VR technology in recent years has made it possible to simulate highly realistic virtual environments for behavioral research. VR is an excellent tool for creating social stimuli that are more controlled than real stimuli, are replicable, and may be impractical or too expensive to attain in the real world (Fox, Arena, & Bailenson, 2009) (Fox, Arena, & Bailenson, 2009). Several recent studies have used immersive virtual reality technology to understand transportation behaviors (e.g. Farooq, Cherchi, & Sobhani (2018) and (Sobhani & Farooq (2018)). The present work adds to this young body of literature, confirming the applicability of VR in transportation research. Use of VR in behavioral studies related to transportation expands possibilities for designing controlled experimental scenarios, and is highly encouraged in future research.

APPENDIX

Table A.1: mixed effect linear model predicting emotional valence rating as a function of the density level

	Estimate	Std. Error	df	t-value	Pr(>|t|)
(Intercept)	4.49	0.40	148.62	11.35	<2e-16
Density	-1.04	0.10	163.00	-10.48	<2e-16
log likelihood	-459.78				

Table A.2: mixed effect linear model predicting emotional arousal rating as a function of the density level

	Estimate	Std. Error	df	t-value	Pr(>|t|)
(Intercept)	7.32	0.20	68.21	35.89	<2e-16
density	0.0024	0.034	163.00	0.073	0.94
log likelihood	-267.91				

Table A.3: mixed effect linear model predicting time perception bias as a function of passenger density

	Estimate	Std. Error	df	t-value	Pr(>|t|)
(Intercept)	-16.31	5.31	58.35	-3.07	0.003
density	1.81	0.74	163.00	2.43	0.02
log likelihood	-905.08				

Table A.4: mixed effects linear model predicting time perception bias as a function of valence.

	Estimate	Std. Error	df	t-value	Pr(>|t|)
(Intercept)	-8.67	5.05	40.72	-1.72	0.09
valence	-1.60	0.44	169.38	-3.67	0.0003
log likelihood	-902.22				

Table A.5: mixed effect linear model predicting perceived travel time as a function of average RR (distance between heart peaks)

	Estimate	Std. Error	df	t-value	Pr(>|t|)
(Intercept)	58.07	27.39	121.78	2.12	0.04
average RR	0.24	37.88	126.51	0.01	1.00
log likelihood	-916.42				

Table A.6: mixed effect linear model predicting travel time estimation bias as a function of average RR

	Estimate	Std. Error	df	t-value	Pr(>|t|)
(Intercept)	22.53	26.37	132.74	-0.854	0.395
average RR	16.36	36.42	138.54	0.449	0.654
log likelihood	-904.02				

Table A.7: mixed effect linear model predicting emotional arousal as a function of average RR

	Estimate	Std. Error	df	t-value	Pr(>|t|)
(Intercept)	6.12	1.06	107.39	5.78	7.60E-08
average RR	1.69	1.47	110.90	1.15	0.25
log likelihood	-263.48				

Table A.8: mixed effect linear model predicting emotional valence from average RR

	Estimate	Std. Error	df	t-value	Pr(>|t|)
(Intercept)	-0.13	1.94	46.68	-0.07	0.95
average RR	2.12	2.70	46.87	0.79	0.44
log likelihood	-498.41				

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