DIGITIZING TRAVEL EXPERIENCE: ASSESSING, MODELING AND VISUALIZING THE EXPERIENCES OF TRAVELERS IN SHARED MOBILITY SERVICES

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During shared travel, humans regularly have negative experiences resulting from unmet needs in terms of safety, comfort, accessibility, efficiency, reliability or information. Frequent negative travel experiences motivate travelers to use private motorized transport instead of more sustainable, shared mobility services. It is difficult for shared transport providers to react to such negative experiences, as these mostly depend on individual needs and situational factors and can therefore rarely be counteracted with static one-size-fits-all solutions. Additionally, (real-time) information about a traveler's experience is not (digitally) available to providers and thus a situation-adapted reaction is often not possible. Therefore, methods to assess travel experience and make travel experience digitally available are highly important for enabling means to render shared transport more attractive. Here, we present initial research on digitizing travel experience exemplified by an envisioned automated shuttle line.

1. INTRODUCTION: DIGITIZING TRAVEL EXPERIENCE

Attracting a larger number of individuals to utilize shared transportation, as opposed to private motorized transport, represents a significant step towards reducing carbon emissions within the mobility sector. However, during shared travel, travelers often encounter negative experiences resulting from unmet needs such as safety, comfort, accessibility, efficiency, reliability, or information (Schiefelbusch, 2015). Frequent negative experiences can make travelers to increasingly opt for private motorized transport while reducing their reliance on shared transportation. Shared transport providers face challenges in responding to these negative experiences, as they involve subjective evaluations influenced by various intrinsic (e.g., number of luggage pieces to carry) and extrinsic (e.g., delays, weather conditions) factors that cannot be effectively addressed through static one-size-fits-all solutions. Complicating matters further, providers lack access to (digital) information regarding the travelers' experience, making it difficult to tailor responses accordingly. Yet, the increase of digitalization in the mobility domain has the potential to remedy this.

In other domains such as industry 5.0, human-centricity is envisioned to be enabled by digital representations of the involved humans including their relevant attributes for a certain task (e.g. Wang et al., 2024). Similarly, digital representations of travelers have been conceived for the mobility domain as digital twins of travelers (e.g. Anda et al., 2021; Rudolph et al., 2022). Such digital twins could become able to collect relevant information about the travelers from apps on smartphones or smartwatches (e.g. trajectories, booked tickets) and combine these with data from schedules or real-time information from vehicles (busses, shuttles etc.). However, in most current concepts, digital representations of travelers almost entirely lack information about travel experiences, so that dynamic changes in travelers' needs cannot be sufficiently accessed and addressed.

Travel experience can be defined as the impressions and subjective evaluations of events occurring throughout a journey encompassing the utilization of services, vehicles, and interaction with traveler interfaces such as hubs, displays, and apps (c.f. Schiefelbusch, 2015; Barría et al., 2023; Bosch et al., 2023). Since such experiences are closely tied to affect and emotions, assessing them requires a combination of multimodal information and contextual knowledge (e.g. Scherer, 2005; Bethge et al., 2021). Hence, travel experience should at best be assessed combining subjective and physiological data (e.g., heart rate) with contextual information (Shoval et al., 2018; Barría et al., 2023). Particularly when aggregated across multiple journeys and travelers, physiological and subjective data can provide insights into recurring moments of positive or negative affect experienced by travelers (Bosch et al., 2023). Contextualized with location information, instances of positive or negative experiences can help identify the causes for these peaks, thus enabling mobility providers to implement measures for improving negative hotspots in travel experiences.

One easily understandable approach for visualizing dynamic location-based data is through map representations (e.g., Google Traffic Layer), which may also be applicable for representing travel experiences. In the past, map representations have been employed to understand how citizens perceive specific routes or sections of cities (Pánek and Benediktsson, 2017; Shoval et al., 2018; Meenar et al., 2019; Camara et al., 2021). Initial efforts have been made in the field of mobility, including the automotive sector (Greco et al., 2015; Dittrich, 2021) and public transport (Castro et al., 2020; Barría et al., 2023; Bosch et al., 2023). Building on this, we present ongoing research focused on developing relevant map representations to visualize travel experiences during shared travel in an easily understandable manner.

In sum, there is a need for methods that render travel experiences accessible to mobility providers in order to enable individualized services or traffic management based on travel experience. Therefore, this work summarizes our ideas and current endeavors for assessing, modeling and visualizing travel experiences based on examples from a shared mobility service, namely a fictive automated shuttle line.

2. EXAMPLE PROJECTS

The work presented here is related to a use case of a future automated shuttle services line, which was partly conceived in the German funded project ViVre (see Touko Tcheumadjeu et al., 2022). In the concept, an automated shuttle is envisioned to operate in the City of Braunschweig, Germany, between the central station and the Airport Braunschweig-Wolfsburg (BWE). Unlike a standard bus line, it is thought to operate as on demand-responsive shuttle without fixed, but flexible virtual stops (e.g. Hub et al., 2023), which means that participants can enter and exit where requested. This shuttle line concept is utilized to exemplify the methods for assessing, modeling and visualizing traveler experience in the following sections. Initially, we describe our work on assessment of travel experience and show map representations illustrating the results of the assessment. Following that, we describe a concept of modeled travel experience on the shuttle line and visualize the changes of travel experience in the model in a map representation.

2.1 Assessment of Travel Experience: Equipment and Visualization

Affective states manifest themselves in changes in speech, facial or body expression, physiology, behavior and subjective experience (Scherer, 2005; Kreibig, 2010). Therefore, variations in travel experiences should be assessed in a multimodal way optimally covering as many as possible of the aforementioned aspects. Yet, the use case of an individual traveler on journeys covering walking and being on board a shuttle constrains the available sensors, especially if the assessment should be extended to intermodal trips in the future. Specifically, the assessment needs to be unobtrusive with wearable devices, such that the entire journey can be covered. Hence in our work, we started the assessment of travel experience based on a combination of location, self-report and cardiological data and tested this approach in a participant study with a Wizard-of-Oz version of an automated shuttle (meaning that a human driver mimicked the automation, for study details see Rybizki et al., 2022 and Brandebusemeyer et al., 2022).

In the study, a smartphone app (based on institute-internal developments) was used to assess self-reported travel experience (operationalized as experienced comfort) via regular prompts (“How is your current comfort level?”) combined with a body-worn electrocardiogram for deriving heart rate (HR) (from Movisens, Karlsruhe, Germany) along the journey. The results of this first study indicate that unpleasant events such as an unexpected and uninformed stop of the shuttle indeed led to measurable changes in self-reported comfort and HR, indicating the potential of our approach to assess travel experience (Brandebusemeyer et al., 2022). The resulting self-report and HR data were then visualized as overlay on a map (see Figure 1). For the visualization, data were averaged across participants in squares of 20x20 meters. Figure 1 illustrates that different parts of the journey are linked to different travel experience. When participants navigate to the virtual bus stop (light grey rectangles at the bottoms) and to the final destination (top rectangles), travel experience is rather low (likely due to difficulties with the navigation app) and heart rate is high (possibly due to a combination of physical activity with negative experiences). When the shuttle stops without informing participants (rectangle termed unexpected stop in the middle) slight changes in travel experience and HR are visible (see also Brandebusemeyer et al., 2022). Together this illustrates that the proposed methods to assess travel experience help to uncover phases of negative pain points, especially when average across groups of travelers.

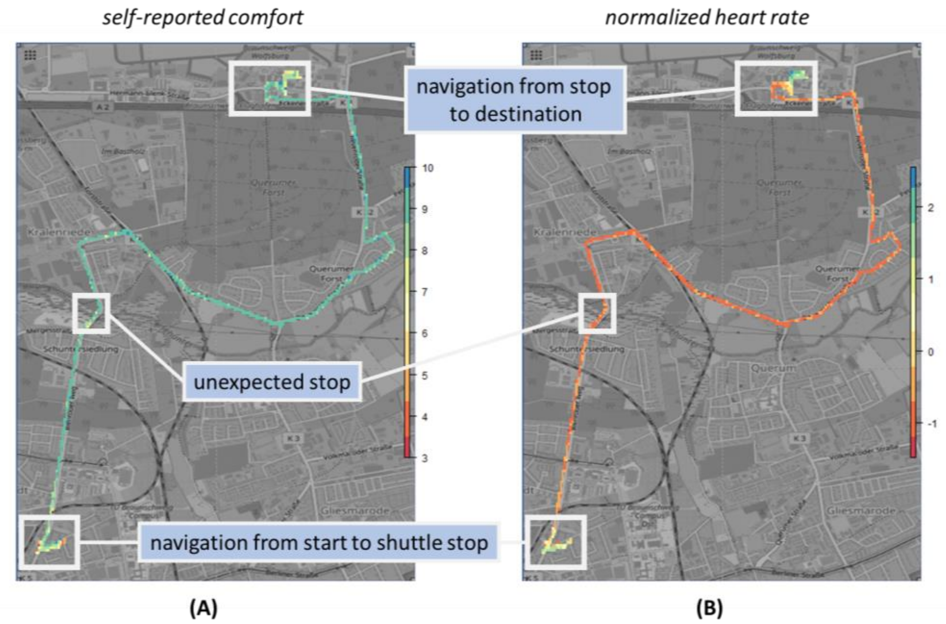

Figure 1. Visualization of collected travel experience data from a Wizard-of-oz participant study on envisioned shuttle line with self-report data on the left (A) and heart rate data on the right (B). Interesting events are marked with light grey rectangles. Participants started navigating from a road side library to a shuttle stop (bottom left), entered the shuttle there and on the way an unexpected stop occurred. Participants were dropped off at BWE and navigated to the destination.

2.2 Towards Modeling Travel Experience: Model Conception and Visualization

Models of travel experience along certain journeys or service lines could be very valuable especially when current services should be adapted or new services ought to be introduced. In such cases, models could be used for forecasts or what-if simulations that allow to pre-evaluate certain measures without actually implementing these. Since such models are barely available yet, we used the aforementioned shuttle line to conceive a model of travel experience. The model is based on the traveler trajectory concept that divides journeys into milestones (Rudolph et al., 2022). The milestones (e.g. arriving at a stop, boarding a shuttle, events such as emergency stops etc.) enable the possibility to integrate steps of a traveler's journey with external information sources (e.g. timetables). Therefore, the trajectory then reflects the expectations of a passenger with regard to the transport task, such as punctuality, ensuring connections and other subjective parameters. In this way, trajectories provide context for relating travel experience with journeys.

Table 1. Events with an effect of travel experience in our model, a description of the effect, potential personal characteristics influencing the effect and the assumed mathematical expression.

Event	*Predicted change in traveler experience*	*Influencing factors, direction of influence*	*Resulting mathematical expression*
Shuttle encounters a traffic jam	Experience depreciates the longer the traffic jam is active	Influence highest for ages 25 – 41, continuous drop-off for older/younger travelers	$sigmoidal\ (time) * Gaussian(age)$
Shuttle has to initiate emergency brake maneuver	Rapid decline in experience, returning to neutral with time	Continually higher influence for travelers older than 40	$gamma(time) * sigmoidal(age)$
A person sits down on the seat next to a traveler	Little depreciation building up over time, returning to neutral after acclimatization occurs	Higher influence if person sitting down also has luggage with them	$(mixture\ of\ exponentials)(time) * exponential(luggage)$
Anticipation to get off shuttle as a traveler's stop is approaching	Slowly appreciating experience until stop is reached	-	$sigmoidal(time)$

For modeling travel experience, the effect of a certain event on a journey on the travel experience of an individual has to be quantified. Note that this entails that certain events influence travel experience and that these effects may be different for different individuals or groups. The literature on travel experience mostly described qualitative effects (like "full busses reduce experienced comfort", "reductions in comfort are stronger for elder persons"), but barely quantified these sufficiently in mathematical expressions. However, modeling travel experience along journeys in relation to trajectories needs such expressions. Hence, we first conducted a small literature research to identify and select a few events that influence travel experience and then developed a suitable mathematical model for each of these events. The selected events include the shuttle being stuck in a traffic jam, the shuttle initiating an emergency brake, the seat next to a traveler being occupied by another, unknown person and a traveler anticipating to leave the shuttle at the final destination (e.g. see Haywood et al., 2017; İmre and Çelebi, 2017; Vicente and Reis, 2018;

Brandebusemeyer et al., 2022; Luther et al., 2023). For these events, we mathematically described – based on educated guesses – the influence of that event on travel experience depending on certain personal characteristics (e.g. age, number of luggage pieces, Table 1 summarizes the events descriptions with our mathematical expressions and Figure 2 illustrates the dynamic effects). At this point it has to be noted that these expressions include certain assumptions and only suggest mathematical exactness for the purpose of a demonstration. Definitely, these formulas need to be verified and improved with real data from user studies.

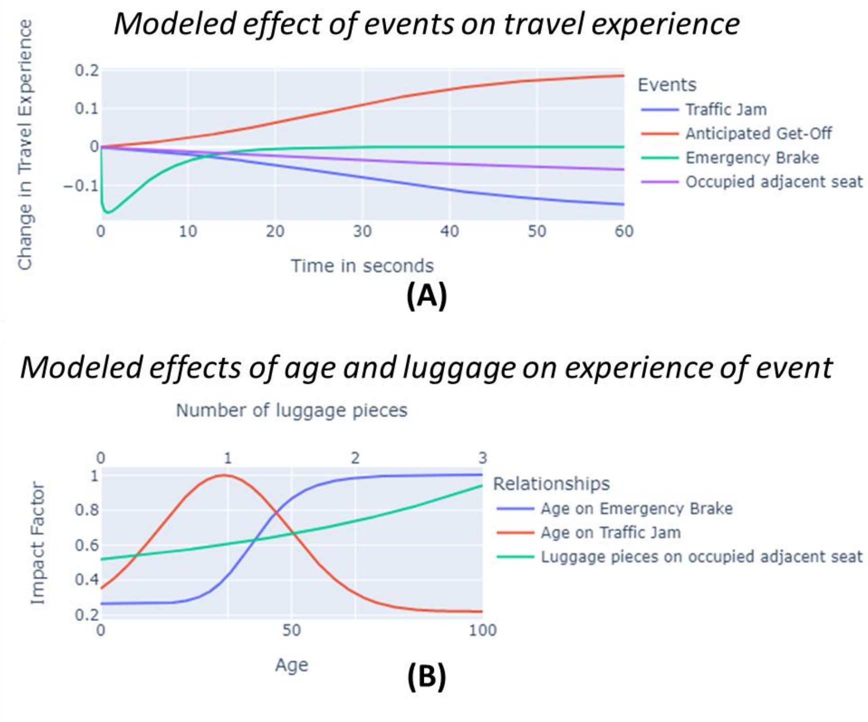

Figure 2. Illustration of modeled effects of selected events on dynamic changes of travel experience (A) and of interaction effects between personal characteristics and events on travel experience (B).

Based on the described trajectory concept and the assumed quantifications, travel experience was modeled for a set of travelers using the abovementioned fictive shuttle line for both directions (central station to BWE, BWE to central station). As outlined above, the travel experience of an individual could be influenced by external events (traffic jam, emergency brake), the number of persons in the shuttle and the individual anticipation of reaching the destination. Furthermore, the traveler's age and number of luggage pieces influenced the evaluation of certain events. Travel experience was quantified for each synthetic passenger separately, each provided with an experience base level. The total travel experience for the shuttle as a whole was then calculated by summing up the individual experiences at each point in time.

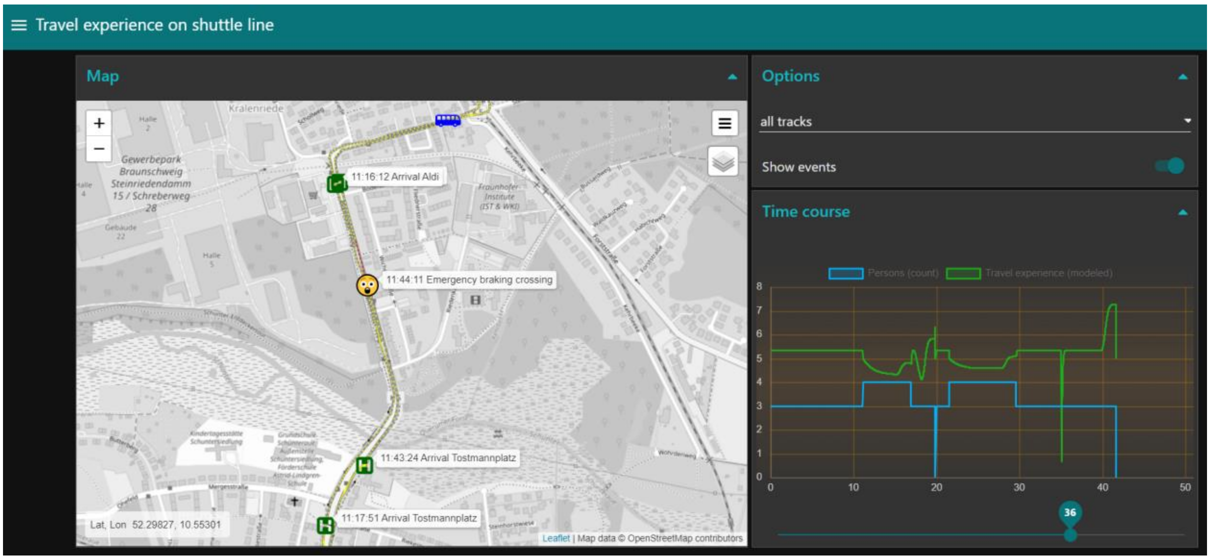

Figure 3. Frontend to visualize the modeled influence to emotions based on events during a journey of passengers using a shuttle. The left window presents the shuttle line with icons referring to certain events. The aggregated travel experience in the shuttle is represented by different colors (from positive travel experience [green] to negative travel experience [red]). On the right, the track to be displayed can be selected and the dynamics of the number of travelers in the vehicle (blue) and the aggregated travel experience (green) are shown.

A custom developed frontend was used for the visualization of model data, which enables a map display with overlays via web browser and offers various selection options to a user analyst (see Figure 3). The basis for this view is recorded tracks of a trip consisting of points that have geographical positions and a time stamp. These trips can be displayed separately or at once. On top of those data we have inserted events that are representing the start of a traveler’s experience change as described before. In this way it’s possible to assign a model value of its current state to each subsequent track point and an individual passenger who takes part in the journey. The frontend displays those data averaged for all journey participants as a colored representation of the individual points on the map. In addition, the modeled influence of the events on the travel experience value (range 0 to 10) and traveler count is presented in a separate chronological chart (Figure 3).

3. DISCUSSION & OUTLOOK

Travel experience can be an important factor for attracting people to use shared mobility services instead of private motorized transport, so that methods for rendering travel experience accessible are desired. We described initial results of our ongoing research approach for assessing, modeling and visualizing the experience of travelers in shared mobility services based on an example of a future automated shuttle line.

We presented our method to assess travel experience based on a combination of self-report and physiological data. The results illustrate the potential of our approach for making episodes of negative travel experiences visible and accessible. However, despite this, there is a lot of research needed for reaching technology readiness levels that allow usage of the method in application settings. For instance, the use of physiological data for understanding affect-related phenomena in settings where people accomplish activities with different metabolic demands (e.g. walking, standing, sitting) is challenging due to the strong effect of physical activity on physiology (e.g. Brouwer et al., 2018). Regarding self-report, it needs to be examined which intervals are adequate for prompting travelers. While in study settings, relatively short intervals below five minutes may be alright (e.g. Bosch et al., 2023), adequate intervals for everyday applications need to be calibrated with caution to keep users engaged. In addition, further sensors for analyzing experiences of travelers could be valuable. Considering emotion theory (e.g. Scherer, 2005), it could help to utilize public cameras or microphones (e.g. on stations or in vehicles) for gaining more information on experience based on facial and body expressions as well as speech data. However, such data may be rather be used to understand collaborative experiences instead of filling individual digital twins of travelers, let alone the data privacy questions arising from such methods. Yet, considering data privacy and sovereignty is also paramount when data from individual travelers are shared with service providers, so that research on suitable software and hardware architectures for assessing, storing and sharing these data is needed. Moreover, concepts for incentivizing travelers to be willing to share their data for higher service quality, lower travel fares or other benefits need to be explored in future.

The presented model of travel experience on the fictive automated shuttle line should be seen as an initial demonstration of the potential of such models. Based on the literature on travel experience, we postulated assumed relationships between certain events, personal characteristics and travel experience with mathematical expressions. Adding these expressions to individual traveler trajectories from earlier concepts (Rudolph et al., 2022) offers the possibility to realize a model of traveler movement integrating travel experiences along entire journeys. Yet, at the moment our model only suggests mathematical exactness that needs to be validated and fine-tuned in future research with data from real travelers. Hence, such models will be able to unfold their full potential if combined with real-time capable methods for assessing travel experience with defined interfaces for data exchange. After being fed with live data, models could also be enabled to provide forecasts or what-if-simulations to test and evaluate future traffic management decision with models.

In sum, here we presented our ongoing research to assess, model and visualize travel experiences during shared mobility services. Our activities can be seen as initial steps in the direction of our vision to realize digital twins of travelers that integrate relevant information about current needs of travelers and eventually will enable to realize more user-focused shared mobility services.

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