THIS IS A PREPRINT VERSION THAT HAS NOT YET BEEN PEER REVIEWED

Identification of user groups of autonomous shuttle buses:

A latent profile analysis

Franziska Hofbauer[1], Peter Fischer[1], Matthias Hudecek[1]

[1]Department of Experimental Psychology, University of Regensburg, Regensburg, Germany

Correspondence address: Chair of Social, Organizational, Working and Business Psychology, Universitätsstraße 1, 93040 Regensburg.

Email: franziska.hofbauer@psychologie.uni-regensburg.de

Abstract

Autonomous driving and its acceptance are becoming increasingly important in psychological research as the application of autonomous functions and artificial intelligence in vehicles increases. In this context, the person of the user is increasingly considered, which is the basis for the successful establishment and use of autonomous vehicles. Numerous studies show an association between personality variables and the acceptance of autonomous vehicles. This makes it more relevant to identify potential user profiles to adapt autonomous vehicles to the user and the needs of the user groups to marketing them effectively. Our study, therefore, addressed the identification of user groups of autonomous vehicles (AVs). A sample of 388 subjects answered questions about their intention to use autonomous buses, their sociodemographics, and various personality variables. Latent Profile Analysis was used to identify four user group profiles that differed significantly from each other in their willingness to use AVs. In total, users with lower anxiety and increased self-confidence were more open toward AVs. Technology affinity as a trait also contributes to the differentiation of user groups and AV acceptance. The profile solutions and the correlations with the intention to use proved to be replicable in cross validation analyses.

Keywords: autonomous driving, artificial intelligence, latent profile analysis, autonomous vehicle acceptance, user groups

Funding Statement

The research was funded by a grant from the Federal Ministry for Digital and Transport (BMDV), Germany (FKZ: 01MM20003F).

Statements and Declarations

All authors declare that they have no conflicts of interest.

Short Biography

Franziska Hofbauer is a PhD candidate at the Chair of Social, Work, Organizational and Economic Psychology, University of Regensburg, Germany. Her main research focuses on the acceptance of autonomous systems with a specialization in autonomous driving systems.

Peter Fischer is a full professor and Chair of Social, Work, Organizational and Economic Psychology at the University of Regensburg, Germany. His main research areas comprise the psychology of digitalization, blockchain, judgment and decision-making, aggressive behavior and prosocial behavior.

Matthias Hudecek is a postdoctoral researcher at the Chair of Social, Work, Organizational and Economic Psychology, University of Regensburg, Germany. His main research areas comprise the acceptance of autonomous systems with a specialization in autonomous driving systems, personality and narrative identity and self-determination theory.

Contribution statement

All authors developed the study concept, contributed to the study design, and interpreted the results. Material testing and data collection were performed by FH and MH. The data were analyzed by FH. FH drafted the manuscript, and MH and PF provided critical revisions. All authors contributed to the article and approved the submitted version.

Introduction

In recent years, psychological research on the acceptance of autonomous driving has increased significantly. In local public transport, the so-called micro-transit, autonomous buses are expected to be part of everyday life as early as 2030 (Litman, 2022). Currently, autonomous micro transit pilot systems are being tested in various fields of application worldwide (e.g., Bernhard et al., 2020). In these test projects, in addition to the technological component, the psychological perspective is increasingly becoming the focus of interest. With their experience and acceptance, the passenger is crucial for establishing autonomous micro-transit systems. The more autonomous driving is adapted to user needs and interests, the easier it can develop into an attractive alternative to non-autonomous driving (Haboucha et al., 2017). It is becoming increasingly clear that personality traits, e.g., extraversion or self-efficacy of potential users are significant factors influencing the intention to use (ITU, Du et al., 2021; Qu et al., 2021; Venkatesh et al., 2012). To map the complexity of personality factors and thus respond best to the needs of potential users, we aim to analyze patterns in personality characteristics and identify user group profiles from them. To the best of our knowledge, there are no extensive empirical studies on this topic until now. The goal of this study is therefore the explorative analysis and identification of user groups of autonomous vehicles (AV) based on selected personal characteristics and dispositions.

Literature Review and Research Framework

The person of the passenger must be taken into account when promoting the acceptance of autonomous driving systems. A vast body of research shows that intrapersonal factors contribute to AV acceptance and ITU. For example, acceptance of autonomous vehicles is significantly related to sociodemographic variables, such as gender (Lemonnier et al., 2020), age (Qu et al., 2021), education (Yuen et al., 2022), and income (Ding et al., 2022). Several previous studies consistently show that males and younger subjects are more receptive to AVs (e.g., Ding et al., 2022; Dong et al., 2019). Gender effects may be due to men reporting a higher general affinity for technology and being more likely to pursue technical careers (Trapani & Hale, 2019). Women, on the other hand, attribute greater discomfort and uncertainty with technology to themselves, possibly due to stereotypical biases (Blasko et al., 2020; Koch et al., 2008). However, acceptance of new technologies such as AVs also appears to be a generational issue. Younger individuals are less concerned about this change in transportation (Charness et al., 2018), but on the other hand have greater concerns about hacking attacks (Garidis et al., 2020). Bonem et al. (2015) found that older individuals rate risks particularly high when the risk addresses health or ethics. It is possible that AV technology, in which artificial intelligence (AI) is responsible for accident-free driving and ethical decision-making, is experienced as more threatening due to its novelty (Cui et al., 2019; Sankeerthana & Raghuram Kadali, 2022). High levels of education and income are also associated with higher technology acceptance (Yuen et al., 2022). Individuals with higher education are in many cases more familiar with new technologies such as AVs due to broader knowledge of technical functions and developments (Yuen et al., 2022). In addition, high levels of education are often associated with higher socioeconomic status and income (Rojas-Méndez et al., 2017). Moreover, the often expensive technological innovations, e.g., the newest smartphones or laptops, can often only be financed if income permits. As a result, individuals with high levels of education and income often have better access to technology, which in turn favors familiarity and adoption (Rojas-Méndez et al., 2017).

In addition to sociodemographics, there is now particularly insightful evidence on personality variables in relation to the adoption of autonomous driving technology. Various studies show significant relationships between classic personality traits such as the Big Five (neuroticism, extraversion, openness, agreeableness, and conscientiousness; Costa & McCrae, 1989) and attitudes toward AVs (e.g., Zhang et al., 2020). As demonstrated in a study by Qu et al. (2021), individuals with high scores in extraversion and openness are more open to AVs, whereas high neuroticism scores negatively affect acceptance. However, Charness et al. (2018) also showed that particularly open-minded users are more willing to relinquish control to the AI in an autonomous vehicle. Particularly conscientious and compatible users showed more concern in this regard, e.g., regarding the reliability and usability of AVs (Qu et al., 2021).

In addition to these classical personality traits, constructs related to one’s attribution of control seem to have an impact on AV acceptance. However, a look at the studies on control beliefs and self-efficacy reveals partly contradictory results. Control beliefs can be located as a construct on a dimension whose extremes are internal and external control beliefs. People differ individually in whether they generally attribute control over situations or facts to themselves (internal) or to external factors (external; Rotter, 1966). According to Choi and Ji (2015), an external control belief contributes positively to ITU. The authors explain this by the fact that, for example, people who do not feel able to participate in traffic under their control or responsibility (e.g., due to physical impairment) prefer to use autonomous vehicles as a means of transportation. Another reason for this could be that people with external control beliefs generally attribute low levels of their control to themselves and thus experience the relinquishment of control to AI as less drastic (Takayama et al., 2011). This is contrasted with a finding by Du et al.(2021) showing that high self-efficacy has a positive effect on trust in AVs and thus ITU.

The authors explain this result by the fact that people with high self-efficacy prefer to accept challenges rather than avoid them and thus react more openly to AVs (Graham, 2011). Since high self-efficacy is associated with internal rather than external locus of control beliefs, the results contradict the finding of Choi and Ji (2015), who found external locus of control beliefs to be a predictor of ITU (Chen & He, 2014). A low general need for control also contributes positively to the ITU (Garidis et al., 2020).

One reason for the contradictory results on own control attribution might be the interaction with other personality traits. Among other things, the acceptance of AVs is also determined by the general disposition to trust (Benleulmi & Blecker, 2017). It is plausible that individuals who have a fundamentally higher level of trust also trust AVs more strongly without needing a high level of their own experience of control. Thus, people with high general trust are more willing to use AVs (Benleulmi & Blecker, 2017). In addition, technology affinity contributes positively to trust in new technologies, which in turn lowers perceptions of potential risks (Choi & Ji, 2015). High technology confidence, in the sense of confidence in one's technological capabilities, is in turn considered a basis for trust in human-machine interaction (Jian et al., 2000). According to Venkatesh (2000), this type of trust also influences the perceived ease of use, which in turn favors the ITU of AVs (Jing et al., 2020).

Another major determinant of AV acceptance is anxiety, although the study results still differ regarding the direction of the relationship. For example, contact with AV technology can create anxiety among potential users due to the novelty of the technology (Fraedrich & Lenz, 2016). Fears about AVs can also reduce the willingness to use AVs (Hohenberger et al., 2017). Based on these results, it would be plausible to assume that high trait anxiety as a stable personality trait is also associated with low AV acceptance. In contrast, the results of Qu et al. (2021) showed a positive correlation between trait anxiety and the acceptance of autonomous driving systems. Anxious people rate the reliability of AVs higher. The authors explain these expected findings by arguing that anxious people would rather hand over control to an autonomous system because they are more afraid of human errors than AI errors (Qu et al., 2021). Regardless of the direction of the association, trait anxiety seems to play a role in AV acceptance. Similar findings also emerged for the so-called technology anxiety. Kopeć et al. (2022) found that higher technology anxiety impairs the acceptance of an autonomous working environment. This association can also be applied to AVs. Keszey (2020) found that both fears of technology in general and specific technological fear (e.g., related to hacking attacks) have a negative impact on AV adoption.

The answer to the question which needs are important for the users of autonomous driving systems and how these can be satisfied is correspondingly complex and cannot be given in a generalized way. Previous research has already identified some personality traits that are predictive of ITU. As described before, it was found that both classic personality traits such as the Big Five (i.e., neuroticism, extraversion, openness, agreeableness, conscientiousness), as well as traits related to technology affinity (e.g., technology competence, acceptance, confidence, and anxiety), are positively related to the acceptance of AVs. In addition, especially variables related to self-confidence (e.g., self-efficacy expectancy, control belief), the disposition to trust, and trait anxiety have a significant effect on the acceptance of AVs. However, to the best of the authors' knowledge, no attempt has yet been made to combine these characteristics and to investigate whether typical response patterns for different user types can be identified. To address interindividual requirements and expectations in AV development and to further adapt AVs to potential passengers, it is important to analyze patterns in selected user characteristics and thus identify user groups. These user groups can present the complex set of user characteristics and needs abstractly and at the same time allow AV providers a more differentiated perspective on their potential passengers. In other contexts, e.g., general public transport (Shrestha et al., 2017) or Bitcoin (Kang et al., 2020), user group analysis has already been successfully applied to better understand target groups from a marketing point of view and thus to better target their needs. Thus, the analysis of different user groups is also desirable in the context of AVs, especially because this technological innovation is expected to affect the general population (Litman, 2022). The aim of this study is therefore the identification and explorative analysis of AV user groups based on the personality variables that were found to be relevant to AV acceptance in previous research: the Big Five, the dispositional technology affinity variables, the self-confidence variables, disposition to trust and trait anxiety. Following the approach of Spurk et al. (2020), our study addresses the following research questions:

1. What is a meaningful and useful number of user groups?

2. How can the different profiles be characterized?

3. How big are the profiles?

4. To what extent is profile affiliation predictive for ITU of AVs?

5. How valid are the results?

Method

Sample

A sample of 388 volunteers (111 male, 276 female, 1 diverse) aged between 18 and 64 was recruited via different online at universities, social media, and personal approach. The participants watched a video of an autonomous bus and then answered the questionnaire. Two people were pre-excluded because they had processed less than 80 % of the questionnaire. *Table 1* shows the sociodemographic characteristics of the final sample. Participation in the study was without payment; students received course credit for participation (students must take part in studies and experiments carried out by researchers of the universities).

***** Please insert Table 1 around here *****

Instrument and profile indices

Based on the current state of research, we selected 16 variables as possible indices for user profiles: 15 of the indices refer to personality, and one variable to age. Age has a significant effect on the acceptance of AVs (Charness et al., 2018). We, therefore, consider it useful to include age when analyzing potential user groups, because it can contribute to a deeper understanding of user group characteristics. This combination should later enable us to place the ITU of customers on AVs in the context of individual personality characteristics. The questionnaires and instruments used are shown in *Table 2*. The basis for the present study was the data of a larger survey on the first impression of autonomous vehicles. Therefore, in addition to the variables mentioned, the following variables were collected: education, area of work, working hours, income, political orientation, neighborhood, motivation for AV use, AV knowledge, expectations, and suggestions for improvement (all self-developed), transport usage habits (adapted from Nordhoff et al., 2019), Satisfaction-with-Travel-Scale (Ettema et al., 2011), facilitating conditions (van der Laan et al., 1997), performance expectations (based on Nordhoff et al., 2018), effort expectations (based on Venkatesh et al., 2012), service and vehicle characteristics (based on Nordhoff et al., 2019), social influence (based on Venkatesh et al., 2012), hedonic motivation (based on Venkatesh et al., 2012), the perceived benefits and risks (Liu et al., 2019), the willingness to share (Nordhoff et al., 2019) and the perceived safety (based on Xu et al., 2018).

***** Please insert Table 2 around here *****

Procedure

The data was collected via an online questionnaire using the *soscisurvey* online application. Driverless buses are too rare in Germany to assume that the respondents have any experience in this area. The video format has already proven to be a useful alternative to the presentation of AV technology in previous studies (e.g., Bjørner, 2015). For this reason, participants who were interviewed online watched a video of 4.5 minutes of a trip with the autonomous bus before answering the questionnaire to get the most comprehensive first impression of the bus possible. This video provides the perspective of a passenger boarding an autonomous bus with other passengers, looking around the shuttle, sitting down, riding in it through several stops, getting off, and watching the autonomous bus drive away. The video is accessible in the online repository. Before processing the actual questionnaire, all participants were informed about the study objective and the protection of their data and then had to confirm their consent for participation. The datasets generated during the current study are available in the OSF repository, https://osf.io/87vr4/?view_only=a4a00679c14f4545b8873ed4d5d56d14.

Statistical analysis

The focus of this study is on a Latent Profile Analysis with subsequent analysis of the relationship between profile affiliation and ITU as well as a validation of the results. For preliminary and descriptive analyses, we used *SPSS* (version 26). The LPA was conducted in *R* (Version 4.1.3; R Core Team, 2022) with the *tidyLPA*- and the *caret-package* via Gaussian mixture modelling (Rosenberg et al., 2018). Possible outliers were checked in advance in boxplots. We did not exclude outliers because the values were within the plausible range, did not represent error outliers, and thus are part of the normal distribution in the population (Leys et al., 2019; Wiggins, 2000). The graphical analysis indicated the normal distribution of the residuals. All data were z-standardized in advance to determine the interpretability of the profiles.

We opted for an LPA followed by regression to investigate differences in ITU in the identified profiles. LPA is a person-centered procedure that identifies latent profiles based on similar response patterns. It enables the probabilistic assignment of each user to the profile with the best fit based on the response pattern (Tein et al., 2013). LPA is therefore particularly well suited for our goal of identifying and distinguishing user groups (Howard & Hoffman, 2018; Woo et al., 2018). The approach allows a subsequent description of various empirically determined user profiles in relation to personality. Our study thus contributes to mapping the knowledge about the person of the users as well as their needs about AVs in a differentiated and multidimensional manner and on this basis to be able to respond more purposefully to their needs, e.g., in the marketing of AVs. For later validation of the profile solution, we randomized the dataset into a training dataset (80 %, n = 315) and a test dataset (20 %, n = 73). To identify the correct number of profiles, we calculated several models in *R* based on the training data set, each with a different number of profiles. We followed the recommendation of Nylund-Gibson and Choi (2018) and started with the model calculation for a single latent profile, after which we gradually increased the number of profiles. We ended this increase after the four-model solution when the profile size fell below the limit of 5 % of the data set for the first time. This procedure, which is common in LPA research (e.g., Kircanski et al., 2017; Ricketts et al., 2018), preserves the practical applicability and interpretability of the profiles because small profile sizes are considered difficult to replicate. We compared the resulting four profile solutions based on predefined criteria with regard to their model fit (Nylund-Gibson & Choi, 2018; Ricketts et al., 2018). We followed the recommendation of Lubke and Neale (2006) and considered the Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC) adapted to the sample size in the form of the Sample-Size-Adjusted Bayesian Information Criterions (saBIC), where low values suggest a better model fit. We also examined the Lo Mendell Rubin Likelihood Test (LMR; Lo et al., 2001). This compares the solution of k profiles with a solution with k-1 profiles. A significant test indicates a better fit of the model with k profiles (Lo et al., 2001; Pastor et al., 2007). The entropy was additionally tested as a measure of the separation reliability of the profiles (Clark & Muthén, 2009). It reflects the mean probability that a person can be correctly classified based on their response pattern within the model with values from .80 being considered very separable (Araújo et al., 2018; Celeux & Soromenho, 1996; Muthén, 2008; Tein et al., 2013). In addition to the statistical parameters, we considered all model solutions under the condition of theoretical plausibility and applicability (Celeux & Soromenho, 1996; Clark & Muthén, 2009). All characteristic values are interpreted with regard to the smallest profile size. To maintain the replicability and practicability of the profile solutions, the minimum accepted profile size is set at 5 % of the data set. Solutions with profiles below this minimum size were declined according to the recommendation of Ferguson et al. (2020). In contrast, profiles above the 5 % threshold indicate remarkable proportions of the profile in the total sample and, accordingly, the relevance of the user group. Subsequently, the procedure was repeated using the test data set to check whether the profile solution found can be replicated. Based on the determined profile solution, the test persons were assigned to the user profile to which they are most likely to belong according to their response pattern. In complementary analyses, the identified profiles were examined descriptively for differences in gender share, degree, income, public transportation use, car ownership, and driver's license ownership. We refrain from introducing names for the profiles because bare designations would be too general and too simple given the probabilistic, complex response patterns. Instead, we assign numbers (1 to 4) to the identified profiles.

To test the predictive validity of the user groups found in relation to the ITU, a regression under 10-fold cross-validation was performed (Reguera-Alvarado et al., 2016). We again randomly split the LPA training data set and performed the regression with a new training data set (80 %, n = 253), and validated the solution using a new test data set (20 %, n = 60). To ensure the highest possible validity within the data sets, we also carried out a 10-fold cross-validation in both data sets. The 10-fold cross-validation is a machine learning method in which the data set is randomly divided into ten blocks. Nine of the blocks would again be used together as a training data set, the tenth block serves as a test data set to validate the results. This procedure was repeated ten times, each time a different block becomes the test data set. Repeating it several times increases the accuracy of the measurement (Wong & Yeh, 2020). In this way, we performed a regression with the independent variable user group and the dependent variable ITU. The mean squared error provides information about the validity of the analysis results as the average distance between the result coefficients of the training and test data sets (Steyerberg et al., 2001).

Results

Latent Profile Analysis

Selection of the most suitable profile solution

The means, standard deviations, and correlations of the variables are shown in *Table 3* in the appendix. Using latent profile analysis, we identified the solution that best fits the data among several possible profile solutions (training data set) and then validated this solution (test data set). We first analyzed a model with one profile within the training data set and gradually added a profile, observing the change in the profile indices. We ended this procedure after the five-profile solution when the smallest profile size fell below the predetermined limit of 5 %. *Table 4* shows the fit indices for the different profile solutions. Thus, the saBIC, the BIC, and AIC decreased as the number of profiles increased, without reaching a low point. We found a similar pattern for the LMR, which reached significance for all profile solutions, indicating a robust model fit. This is a known phenomenon in the literature on LPA and is caused by the fact that adding further profiles provides more information (Masyn, 2013). There is no fixed value above which a reduction in the information criteria is considered insignificant, which affects the interpretability of the indices (Ferguson et al., 2020). Therefore, in these cases, the course of the indices is visualized in so-called Elbow plots (Nylund-Gibson & Choi, 2018). The kink or elbow of the plot reveals the profile solution from which the decrease of the index flattens out. This profile solution, therefore, promises the highest possible, if not the maximum, model fit with the simultaneous economy of the profiles (Masyn, 2013). Therefore, based on the results, during the evaluation we decided to consider elbow plots for the information criteria, which are shown in *Fig. 1a*. The graph follows a consistent downward trend. A slight elbow can be seen for the model with two profiles, suggesting that the two-profile solution fits better. This finding was contrasted with the analysis of the smallest profile size. While the smallest profile in the two-profile solution accounted for 45.0 %, the smallest profile in the three-profile solution at 16.0 %, and in the four-profile solution at 11.5 %, each still account for a substantial portion of the data set. With the addition of a fifth profile, the share of the smallest profile dropped to 4.5 % of the data, i.e., below the predefined 5.0 % limit. Entropy exceeded .80 as a measure of classification confidence only for the four- and five-profile solutions above which it is classified as highly discriminative (Celeux & Soromenho, 1996; Muthén, 2008; Tein et al., 2013). Our goal to identify potential user groups as differentiated and precisely as possible while maintaining economic efficiency is thus best met by the four-profile solution since it has a high degree of classification reliability. In addition, the fourth profile takes up significant proportions that we want to consider. Given the continuously decreasing information criteria and the permanently significant LMR value, we opted for the four-profile solution in the training data set.

Validation of the profile solution

To validate the profile solution, we conducted the LPA analogously with the test data set. The fit indices are shown in *Table 3*. As with the training data set, we ended the analysis with the four-profile solution, in which the smallest profile fell below the minimum share of 5 % for the first time. The analysis of the fit indices also revealed a similar picture that supports our decision for the four-profile solution. Again, the LMR value remained significant across all solutions. The AIC and the saBIC decreased as the number of profiles increased (see elbow plot in *Fig. 1b*). In contrast to the training analysis, the BIC for the three-profile solution reached a low point. The BIC was therefore explicitly in favor of the three-profile solution, as was the Elbow plot of the AIC and the saBIC. The entropy, whose value was recognizably higher than those of the training analysis, exceeded the critical value of .80 for all profile solutions and thus confirmed the classification reliability. In addition to the three-profile solution (16.0 %), the smallest profile still took a remarkable share in the four-profile solution with 13.3 %. With 4.0 %, the size of the fifth profile was again below the acceptance threshold. Although the information criteria of the test data were in favor of the three-profile solution, the addition of the fourth profile granted a higher differentiation with at the same time very good classification reliability and represented with its size of 13.3 % a remarkable share of the data. Under these aspects, the choice fell again on the four-profile solution. With the aforementioned limitations regarding the information criteria, our profile decision thus proved to be replicable and valid.

***** Please insert Figures 1a and 1b around here *****

***** Please insert Table 4 around here *****

Description of profiles

The LPA allows the probabilistic classification of each person to a profile based on their response pattern. In the next step, each training data set was thus assigned to the profile to which it belongs with the highest probability according to its response pattern. The four identified profiles were then compared and interpreted based on their underlying personality traits. *Fig. 2* provides an overview of the mean variable expressions of the four different groups. All four profiles differ in their characteristics. This supports the decision that the number of four profiles is necessary to represent the profiles in a sufficiently differentiated way. We refrain from introducing names for the profiles because naming would be too simplistic with regard to the probabilistic, complex response patterns.

User group 1 accounted for the smallest proportion of the examined sample, with n = 36. It was characterized by increased levels in the anxiety-related scales (neuroticism, trait anxiety, and technology anxiety), while the remaining variables were rather low in comparison. Complementing the high anxiety, individuals in user group 1 exhibited lower-than-average self-efficacy and internal control beliefs. The group also turned out to have a rather low affinity for technology, although the scores of the technology-related variables were within one standard deviation. User group 1 was with M = 24.89 (SD = 4.83) years the youngest group. Further analysis of sociodemographics showed that this group also had the highest proportion of females (86.11 %) and the highest educational qualification (M = 5.02, SD = 1.04). At the same time, the proportion of people with a car (55.56 %) or a driver's license (83.33 %) was the lowest in this group.

User group 2 (n = 66) was also characterized by increased anxiety-related scores. Unlike user group 1, neuroticism and trait anxiety were less pronounced. Rather, this group showed the highest values of technology anxiety. This corresponded with a low affinity for technology, especially with a strikingly low technology competence. In addition, individuals in user group 2 attributed relatively low levels of control to the external environment. At 25.95 (SD = 7.61) years, the age of the associated individuals was in line with the sample average, with again a relatively high proportion of women (80.30 %). The user group also reported the highest level of acceptance of using public transportation compared to the other groups (M = 4.22, SD = 1.73).

The response pattern of user group 3 (n = 145) was primarily characterized by average expressions in all variables. Nevertheless, it showed slightly increased technology competence and relatively low technology anxiety, with both expressions within one standard deviation. The age of the group was also close to the sample average with M = 26.26 (SD = 7.16). Further analyses revealed that members of user group 3 enjoyed public transportation use the least compared to the other groups (M = 3.52, SD = 1.74).

User group 4 (n = 66) showed a response pattern that was opposite in its characteristics to the pattern of user group 1. It was noticeably less anxious. A particularly noteworthy difference was the strikingly low technology anxiety and high technology affinity of user group 3, which clearly distinguished it from the other two groups. This corresponded with increased openness to change, extraversion and conscientiousness. In addition, the group rated its self-efficacy and internal and external control beliefs higher. User group 4 was also the oldest group on average (M = 27.55, SD = 7.75) with the highest proportion of men (42.42 %) and the highest income (10.61 % earned more than 60,000€). Individuals in this group were more likely to own a driver's license (95.45 %) and own a car (77.27 %) compared to the other groups.

***** Please insert Figure 2 around here *****

Relationship analysis between profile affiliation and ITU

We next used regression analyses to check the extent to which the four profiles were predictive of ITU. For this purpose, we again divided the training data set used in the LPA into a new training data set (80 %, n = 253) and a new test data set (20 %, n = 60), the latter serving for validation purposes. Within the training data set, we used ten-fold cross-validation to validate the results. Profile membership significantly predicted ITU, $F(3, 249) = 7.36$, $p < .001$, $R^2 = .08$.

Compared to user group 1, individuals in user group 2 had a 0.33 lower ITU, $t(259) = -1.15$, $p = .252$, and individuals in user group 3 had a 0.18 higher ITU, $t(259) = 0.69$, $p = .492$, although the differences were not significant. For user group 4, ITU was significantly higher by 0.78, $t(259) = 2.75$, $p = .001$. The ITU of user group 2 was again significantly different from the ITU of user group 3, $b = 0.51$, $t(259) = 2.46$, $p = .015$, and from the ITU of user group 4, $b = 1.12$, $t(259) = 4.61$, $p <$ 001. The difference between user groups 3 and 4 was also significant, with the ITU of user group 3 being 0.31 lower, $t(259) = -2.98$, $p = .003$. Thus, user group 4 showed the highest ITU, followed by user groups 3 and 1. User group 2 had the lowest ITU.

Using the regression coefficients, we next predicted the ITU for the test data set as a function of profile membership. The RMSE revealed an average difference of 1.26 between the predicted and the actual value of ITU. The RMSE revealed a moderate average difference of 1.39 between the predicted and the actual value of the seven-point ITU scale (James et al., 2021).

Discussion

Summary and practical implications

Our study aimed to identify possible AV user groups and their predictive power in relation to the ITU. For this purpose, we have performed an LPA with subsequent validation. Our study differs from previous research in several aspects. First, we did not focus on a specific area of personality but tried to depict the user groups as comprehensively as possible in their personality. Based on current research and theories on AVs, we selected the most crucial personality traits for the ITU and used them in an LPA as indices for rich, meaningful user profiles. Second, we tested these user groups directly for their predictive power for AVs' ITU to ensure their practical relevance. As a result, our user groups have already been confirmed for the first time in their practical applicability concerning AVs. Third, we underpinned each of our analysis steps with a validation analysis to ensure the reliability of our results and thus the quality of our study. The validation confirmed our findings almost completely and thus supports the replicability and validity of our results. We put great emphasis on differentiating the profiles as much as possible while maintaining clarity and practicality. We were able to identify four AV user groups and placed them in the context of their ITU. The profiles have characteristic differences, but also similarities. Regarding ITU, it is relevant to which of the identified profiles a user belongs. The user groups and their predictive power for the ITU proved to be valid in our analyses.

The core and largest contribution of our study was the identification of four user groups that differed significantly in their profile characteristics. Particularly important indices of profile affiliation were the variables of self-confidence (i.e., self-efficacy, internal and external control belief), general anxiety (neuroticism and trait anxiety), an affinity for technology (i.e., technology acceptance, competence, and control belief), technology anxiety and trust in technology. This resulted in four different profiles.

People in user group 1 were characterized by a high level of general anxiety and insecurity, with a slightly below-average affinity for technology and increased fear of technology. Thus, self-insecurity in this group might have a negative impact on perception, or new technologies could be more likely to be experienced as threatening or risky. AV marketing could address the needs of this relatively anxious user group by emphasizing the safety-related benefits of AVs (e.g., reducing the likelihood of accidents; Yu et al., 2019). In this context, it should be made clear to what extent AV technology contributes positively to road safety. To reduce potential fears with corrective (positive) experiences, it is necessary to encourage this group to actively use AVs. However, due to general anxiety, people in user group 1 may be more likely to avoid AV use. AV providers should accordingly create ride offerings that are as low-threshold as possible and promise high utility for the group so that the benefits of the ride outweigh the costs of anxiety. Autonomous buses, for example, could be offered temporarily or permanently as a free alternative to paid public transit. Transit agencies could also use reinforcement mechanisms, such as distributing small reinforcing giveaways at the end of a test ride (Angermeier et al., 1994). Similarly, autonomous buses could be offered as free transportation to positively associated destinations, e.g., to the swimming pool or cinema, to generate or increase a positive perception of the bus trip. For this user group in particular, a temporary deployment of service personnel in the bus interior could also make the switch to AV technology easier, to mitigate the potentially anxiety-inducing transition to driverlessness (Dong et al., 2019).

In contrast to user group 1, user group 2 was characterized less by general anxiety and more by strong technology anxiety and a low affinity for technology. The external control belief was low (analogous to user group 1). It is possible that user groups 1 and 2 attributed less control to the external AI technology than to themselves and were therefore less convinced of AVs. To give users control options in the autonomous bus, warning systems could be installed in buses, for example, so that passengers can contact the transport operations center in an emergency (Dong et al., 2019). Nordhoff et al. (2020) have shown in a qualitative setting that an emergency button inside the vehicle contributes to the perceived safety in autonomous buses. Information on driving safety and AV functionality could also be helpful for user group 2. Manufacturers could provide training to help users to better understand AVs and reduce potential technology anxiety. Compared to user group 1, however, the focus in this group should be on providing simple and understandable information, taking into account the low affinity for technology. Manufacturers should also make the handling of AVs as intuitive as possible due to the lower level of technical competence. They should also counter the low confidence in new technologies by making AVs as predictable as possible for this user group, e.g., by using monitors inside the vehicle that transmit the stimulus detection and response of the AV sensors in real-time (Yuen et al., 2022). In addition, transit agencies should focus primarily on reliable, trusted manufacturers to increase the AV trust of the technology-critical group (Yuen et al., 2022).

For user group 3, a relatively average response pattern emerged across the variables, with slightly increased technology competence and slightly decreased technology anxiety. The group showed an average ITU, although their members were less likely in general to use public transport. It is possible, therefore, that the ITU for autonomous cars would be even higher than in our study related to autonomous buses. This group is thus likely to be more of a target group for autonomous cars. Overall, this group can nevertheless be expected to adopt autonomous buses. From a marketing perspective, little consideration of potential fears or skepticism is necessary according to our model. Rather, this group could be further encouraged in their motivation to use AVs by highlighting possible benefits and the fun of driverless driving, e.g., in advertising. However, no in-depth knowledge of AV technology should be assumed.

The profile of user group 4 differed from that of user group 1 in almost all variables. The group was characterized by pronounced self-confidence, low anxiety, and a high affinity for technology in every respect. It seems plausible that members of user group 4, i.e., people with self-confidence attribute better-coping skills to themselves and are less anxious. As a result, they may be more open to new technology. Accordingly, this group was most likely to use AVs. Given their high extraversion and openness, this user group could be further encouraged to use AVs by highlighting social and sustainable aspects of autonomous ridesharing services. With their openness to technologies and AVs, this user group also has great potential to act as a multiplier for AVs. Sharma and Mishra (2022) showed in their study that peer influence can have an even greater impact on AV adoption than media marketing. Accordingly, user group 4 could be suitable for introducing skeptical target groups, such as user groups 1 and 2, to AVs and motivating them to use it. This could be both, for example, in private or via public reports of positive experiences in social media.

Overall, the four user groups showed a very heterogeneous pattern of characteristics and willingness to use AVs. Specially for user groups 1 and 2, AVs were still associated with anxiety. These results are a significant sign that the transition from conventional vehicles to AVs must be gradual to pick up AV-skeptical groups and get them accustomed to the new technology. A too abrupt changeover could lead to overwhelming people in user groups 1 or 2 and thus frustrating them right from the start. Manufacturers and public transport operators should therefore not implement the system too quickly and should define specific measures in advance to meet the needs of each of the four user groups.

Limitations and outlook

To be able to classify the results of our study in a well-founded manner, possible limitations of our study must be reflected, too. First, it should be noted that our sample was not balanced in terms of gender, age, or experience with AVs. To ensure a meaningful user analysis, we aimed for the largest possible sample, for which we were dependent to a significant extent on the recruitment of students who completed the study participation as part of their studies. This is due to the relatively young sample and is presumably also responsible for the predominance of female participants due to the focus on psychology. Due to the high proportion of participants with a comparatively high level of education, it can also be assumed that the sample tends to have more knowledge or experience with new technologies and was therefore relatively open to AVs (Ding et al., 2022). Edelmann et al. (2021) showed that different cultures differ in their AV acceptance. We, therefore, consider it important to replicate the study in different socio-demographic contexts and, in addition, to examine the cultural generalizability through studies in other countries. Furthermore, the study findings should be verified under real-life conditions as soon as autonomous buses are widely available. In our study, the recruitment of test persons under real conditions with the desired sample size proved to be almost impossible due to the anti-Coronavirus measures applicable at the time of the survey and the limited availability of autonomous shuttle buses. For this reason, we opted for a sample, which was shown a video of the autonomous bus. In previous studies, this type of presentation has also proven to be representative (e.g., Lemonnier et al., 2020). However, we cannot guarantee that relatively abstract technologies such as AI and AVs have been sufficiently illustrated by the videos in this study. It will be the necessary task of future studies to investigate this question.

In terms of statistical analysis, our studies have the characteristic limitations of LPA. On the one hand, LPA is a probabilistic procedure. Therefore, the results represent probabilities and not absolute values. Our class assignments are highly likely to apply, but LPA does not guarantee the correctness of our solutions. Regarding the model decision, it must be noted that most our information criteria did not reach a low point for any of the model solutions considered and that the likelihood parameters remained significant. This suggests that each additional profile provided insights. According to Nylund-Gibson and Choi (2018), however, the steady decline can also be an indication that the chosen mixture model is not a perfect model for our data. To make a profile decision, we therefore relied on a combination and best possible matching of the fit indices under consideration of the profile size, which best supported the four-profile solution. It must be mentioned that we selected several parameters for the assessment of the fit and brought them into a decision hierarchy. However, there are no uniform rules for this approach. In this study, we followed current recommendations and best practices from simulation studies. Nevertheless, the profile decision and the interpretation are also subject to a subjective decision-making framework that the LPA entails. The classification of the profiles is also essentially dependent on the separation potential of the used items (Nylund-Gibson & Choi, 2018). With our results, we have now made a first contribution to measuring the separation potential of our items. One task of future studies may be to further refine the findings and the item pool.

Conclusion

Personality plays a significant role in AV acceptance. Our study went beyond these previous findings and integrated them by identifying four user groups based on the most relevant personality traits. Our results allow us to draw implications about the characteristics of the four user groups and how to respond to them in the development and marketing of AVs. Manufacturers and transit agencies should avoid a too abrupt transition to AV technology to avoid alienating user groups with potential fears. An implementation concept tailored to the user groups can help to meet the individual needs of each of the four user groups. Thus, our study provides important contributions from a psychological perspective to the dissemination and acceptance of AVs.

References

Angermeier, W. F., Bednorz, P., Hursh, S. R., Dinsmoor, J. A., Eider, S. T., Elsmore, T. F., Galbicka, G., Hörster, W., Lashley, J. K., Raslear, T. G., Redmon, W. K., & Staddon, J. E. (1994). *Operantes Lernen: Methoden, Ergebnisse, Anwendung. Ein Handbuch*. Reinhardt. https://doc1.bibliothek.li/aab/000a074020.pdf

Araújo, A. M., Assis Gomes, C. M., Almeida, L. S., & Núñez, J. C. (2018). A latent profile analysis of first-year university students' academic expectations. *Anales De Psicología*, *35*(1), 58–67. https://doi.org/10.6018/analesps.35.1.299351

Beierlein, C., Kovaleva, A., Kemper, C. J., & Rammstedt, B. (2012). *Ein Messinstrument zur Erfassung subjektiver Kompetenzerwartungen: Allgemeine Selbstwirksamkeit Kurzskala (ASKU)*. GESIS.

Benleulmi, A. Z., & Blecker, T. (2017). Investigating the factors influencing the acceptance of fully autonomous cars. In *Digitalization in Supply Chain Management and Logistics: Smart and Digital Solutions for an Industry 4.0 Environment. Proceedings of the Hamburg International Conference of Logistics (HICL)* (Vol. 23, pp. 99–115). Berlin: epubli GmbH. https://doi.org/10.15480/882.1449

Bernhard, C., Oberfeld, D., Hoffmann, C., Weismüller, D., & Hecht, H. (2020). User acceptance of automated public transport. *Transportation Research Part F: Traffic Psychology and Behaviour*, *70*, 109–123. https://doi.org/10.1016/j.trf.2020.02.008

Bjørner, T. (2015). *A Priori User Acceptance and the Perceived Driving Pleasure in Semi-autonomous and Autonomous Vehicles*. Paper presented at European Transport Conference 2015, Frankfurt, Germany.

Blasko, D. G., Lum, H. C., & Campbell, J. (2020). Gender Differences in Perceptions of Technology, Technology Readiness, and Spatial Cognition. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *64*(1), 1395–1399. https://doi.org/10.1177/1071181320641333

Bonem, E. M., Ellsworth, P. C., & Gonzalez, R. (2015). Age Differences in Risk: Perceptions, Intentions and Domains. *Journal of Behavioral Decision Making*, *28*(4), 317–330. https://doi.org/10.1002/bdm.1848

Celeux, G., & Soromenho, G. (1996). An entropy criterion for assessing the number of clusters in a mixture model. *Journal of Classification*, *13*(2), 195–212. https://doi.org/10.1007/BF01246098

Charness, N., Yoon, J. S., Souders, D., Stothart, C., & Yehnert, C. (2018). Predictors of Attitudes Toward Autonomous Vehicles: The Roles of Age, Gender, Prior Knowledge, and Personality. *Frontiers in Psychology*, *9*, Article 2589. https://doi.org/10.3389/fpsyg.2018.02589

Chen, H., & He, G. (2014). The effect of psychological distance on intertemporal choice and risky choice. *Acta Psychologica Sinica*, *46*(5), 677–690.

Choi, J. K., & Ji, Y. G. (2015). Investigating the Importance of Trust on Adopting an Autonomous Vehicle. *International Journal of Human-Computer Interaction*, *31*(10), 692–702. https://doi.org/10.1080/10447318.2015.1070549

Clark, S. L., & Muthén, B. (2009). *Relating latent class analysis results to variables not included in the analysis*. https://www.statmodel.com/download/relatinglca.pdf

Costa, P. T., & McCrae, R. R. (1989). *NEO PI/FFI manual supplement for use with the NEO Personality Inventory and the NEO Five-Factor Inventory*. Psychological Assessment Resources.

Cui, J., Liew, L. S., Sabaliauskaite, G., & Zhou, F. (2019). A review on safety failures, security attacks, and available countermeasures for autonomous vehicles. *Ad Hoc Networks*, *90*, 101823. https://doi.org/10.1016/j.adhoc.2018.12.006

Ding, Y., Li, R., Wang, X [Xiaokun], & Schmid, J. (2022). Heterogeneity of autonomous vehicle adoption behavior due to peer effects and prior-AV knowledge. *Transportation*, *49*(6), 1837–1860. https://doi.org/10.1007/s11116-021-10229-w

Dong, X., DiScenna, M., & Guerra, E. (2019). Transit user perceptions of driverless buses. *Transportation*, *46*(1), 35–50. https://doi.org/10.1007/s11116-017-9786-y

Du, H., Zhu, G., & Zheng, J. (2021). Why travelers trust and accept self-driving cars: An empirical study. *Travel Behaviour and Society*, *22*, 1–9. https://doi.org/10.1016/j.tbs.2020.06.012

Edelmann, A., Stümper, S., & Petzoldt, T. (2021). Cross-cultural differences in the acceptance of decisions of automated vehicles. *Applied Ergonomics*, *92*, 103346. https://doi.org/10.1016/j.apergo.2020.103346

Ettema, D., Gärling, T., Eriksson, L., Friman, M., Olsson, L. E., & Fujii, S. (2011). Satisfaction with travel and subjective well-being: Development and test of a measurement tool. *Transportation Research Part F: Traffic Psychology and Behaviour*, *14*(3), 167–175. https://doi.org/10.1016/j.trf.2010.11.002

Ferguson, S. L., G. Moore, E. W., & Hull, D. M. (2020). Finding latent groups in observed data: A primer on latent profile analysis in Mplus for applied researchers. *International Journal of Behavioral Development*, *44*(5), 458–468. https://doi.org/10.1177/0165025419881721

Fraedrich, E., & Lenz, B. (2016). Societal and Individual Acceptance of Autonomous Driving. In M. Maurer, J. C. Gerdes, B. Lenz, & H. Winner (Eds.), *Autonomous Driving* (pp. 621–640). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-662-48847-8_29

Garidis, K., Ulbricht, L., Rossmann, A., & Schmäh, M. (2020). Toward a User Acceptance Model of Autonomous Driving. In T. Bui (Ed.), *Proceedings of the Annual Hawaii International Conference on System Sciences, Proceedings of the 53rd Hawaii International Conference on System Sciences.* Hawaii International Conference on System Sciences. https://doi.org/10.24251/HICSS.2020.170

Gefen, D., & Straub, D. W. (2004). Consumer trust in B2C e-Commerce and the importance of social presence: experiments in e-Products and e-Services. *Omega*, *32*(6), 407–424. https://doi.org/10.1016/j.omega.2004.01.006

Graham, S. (2011). Self-efficacy and academic listening. *Journal of English for Academic Purposes*, *10*(2), 113–117. https://doi.org/10.1016/j.jeap.2011.04.001

Haboucha, C. J., Ishaq, R., & Shiftan, Y. (2017). User preferences regarding autonomous vehicles. *Transportation Research Part C: Emerging Technologies*, *78*, 37–49. https://doi.org/10.1016/j.trc.2017.01.010

Hohenberger, C., Spörrle, M., & Welpe, I. M. (2017). Not fearless, but self-enhanced: The effects of anxiety on the willingness to use autonomous cars depend on individual levels of self-enhancement. *Technological Forecasting and Social Change*, *116*, 40–52. https://doi.org/10.1016/j.techfore.2016.11.011

Howard, M. C., & Hoffman, M. E. (2018). Variable-Centered, Person-Centered, and Person-Specific Approaches. *Organizational Research Methods*, *21*(4), 846–876. https://doi.org/10.1177/1094428117744021

Jakoby, N., & Jacob, R. (1999). Messung von internen und externen Kontrollüberzeugungen in allgemeinen Bevölkerungsumfragen. *ZUMA Nachrichten*, *23*(45), 61–71.

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2021). *An introduction to statistical learning: With applications in R* (Second edition). *Springer texts in statistics*. Springer. https://search.ebscohost.com/login.aspx?direct=true&scope=site&db=nlebk&db=nlabk&AN=2985424

Jian, J.-Y., Bisantz, A. M., & Drury, C. G. (2000). Foundations for an Empirically Determined Scale of Trust in Automated Systems. *International Journal of Cognitive Ergonomics*, *4*(1), 53–71. https://doi.org/10.1207/S15327566IJCE0401_04

Jing, P., Xu, G., Chen, Y., Shi, Y., & Zhan, F. (2020). The Determinants behind the Acceptance of Autonomous Vehicles: A Systematic Review. *Sustainability*, *12*(5), 1719. https://doi.org/10.3390/su12051719

Kang, K., Choo, J., & Kim, Y. (2020). Whose Opinion Matters? Analyzing Relationships Between Bitcoin Prices and User Groups in Online Community. *Social Science Computer Review*, *38*(6), 686–702. https://doi.org/10.1177/0894439319840716

Keszey, T. (2020). Behavioural intention to use autonomous vehicles: Systematic review and empirical extension. *Transportation Research Part C: Emerging Technologies*, *119*. https://doi.org/10.1016/j.trc.2020.102732

Kircanski, K., Zhang, S., Stringaris, A., Wiggins, J. L., Towbin, K. E., Pine, D. S., Leibenluft, E., & Brotman, M. A. (2017). Empirically derived patterns of psychiatric symptoms in youth: A latent profile analysis. *Journal of Affective Disorders*, *216*, 109–116. https://doi.org/10.1016/j.jad.2016.09.016

Koch, S. C., Müller, S. M., & Sieverding, M. (2008). Women and computers. Effects of stereotype threat on attribution of failure. *Computers & Education*, *51*(4), 1795–1803. https://doi.org/10.1016/j.compedu.2008.05.007

Kopeć, M., Fijalkowska, J., & Roszyk, K. (2022). Analysis of the Impact of the Fear of Technology of Warehouse Employees on the Level of their Acceptance of Work in an Automated Environment. *EUROPEAN RESEARCH STUDIES JOURNAL*, *XXV*(Issue 2B), 277–285. https://doi.org/10.35808/ersj/2960

Körner, A., Geyer, M., Roth, M., Drapeau, M., Schmutzer, G., Albani, C., Schumann, S., & Brähler, E. (2008). Persönlichkeitsdiagnostik mit dem NEO-Fünf-Faktoren-Inventar: Die 30-Item-Kurzversion (NEO-FFI-30). *PPmP - Psychotherapie Psychosomatik Medizinische Psychologie*, *58*(6), 238–245. https://doi.org/10.1055/s-2007-986199

Lemonnier, A., Adelé, S., & Dionisio, C. (2020). The determinants of acceptability and behavioural intention of automated vehicles – a review. *Le Travail Humain*, *83*(4), 297. https://doi.org/10.3917/th.834.0297

Leys, C., Delacre, M., Mora, Y. L., Lakens, D., & Ley, C. (2019). How to Classify, Detect, and Manage Univariate and Multivariate Outliers, With Emphasis on Pre-Registration. *INTERNATIONAL REVIEW of SOCIAL PSYCHOLOGY, 32*(1), Article 5. https://doi.org/10.5334/irsp.289

Litman, T. (2022). *Autonomous vehicle implementation predictions: Implications for Transport Planning*. Victoria Transport Policy Institute.

Liu, P., Yang, R., & Xu, Z. (2019). Public Acceptance of Fully Automated Driving: Effects of Social Trust and Risk/Benefit Perceptions. *Risk Analysis*, *39*(2), 326–341. https://doi.org/10.1111/risa.13143

Lo, Y., Mendell, N. R., & Rubin, D. B. (2001). Testing the number of components in a normal mixture. *Biometrika*, *88*(3), 767–778. https://doi.org/10.1093/biomet/88.3.767

Lubke, G., & Neale, M. C. (2006). Distinguishing Between Latent Classes and Continuous Factors: Resolution by Maximum Likelihood? *Multivariate Behavioral Research*, *41*(4), 499–532. https://doi.org/10.1207/s15327906mbr4104_4

Lück, H. E., & Timaeus, E. (1969). Skalen zur Messung manifester Angst (MAS) und sozialer Wünschbarkeit (SDS-E und SDS-CM). *Diagnostica*, *15*, 134–141.

Masyn, K. E. (2013). Latent class analysis and finite mixture modeling. In T. D. Little (Ed.), *The Oxford handbook of quantitative methods* (2nd ed., pp. 551–611). Oxford University Press.

Muthén, B. O. (2008, November 21). *What is a good value of entropy*. http://www.statmodel.com/discussion/messages/13/2562.html?1237580237

Neyer, F. J., Felber, J., & Gebhardt, C. (2012). Entwicklung und Validierung einer Kurzskala zur Erfassung von Technikbereitschaft. *Diagnostica*, *58*(2), 87–99. https://doi.org/10.1026/0012-1924/a000067

Nordhoff, S., Kyriakidis, M., van Arem, B., & Happee, R. (2019). A multi-level model on automated vehicle acceptance (MAVA): A review-based study. *Theoretical Issues in Ergonomics Science*, *20*(6), 682–710. https://doi.org/10.1080/1463922X.2019.1621406

Nordhoff, S., Stapel, J., van Arem, B., & Happee, R. (2020). Passenger opinions of the perceived safety and interaction with automated shuttles: A test ride study with 'hidden' safety steward. *Transportation Research Part a: Policy and Practice*, *138*, 508–524. https://doi.org/10.1016/j.tra.2020.05.009

Nordhoff, S., Winter, J. de, Madigan, R., Merat, N., van Arem, B., & Happee, R. (2018). User acceptance of automated shuttles in Berlin-Schöneberg: A questionnaire study. *Transportation Research Part F: Traffic Psychology and Behaviour*, *58*, 843–854. https://doi.org/10.1016/j.trf.2018.06.024

Nylund-Gibson, K., & Choi, A. Y. (2018). Ten frequently asked questions about latent class analysis. *Translational Issues in Psychological Science*, *4*(4), 440–461. https://doi.org/10.1037/tps0000176

Pastor, D. A., Barron, K. E., Miller, B. J., & Davis, S. L. (2007). A latent profile analysis of college students' achievement goal orientation. *Contemporary Educational Psychology*, *32*(1), 8–47. https://doi.org/10.1016/j.cedpsych.2006.10.003

Qu, W., Sun, H., & Ge, Y. (2021). The effects of trait anxiety and the big five personality traits on self-driving car acceptance. *Transportation*, *48*(5), 2663–2679. https://doi.org/10.1007/s11116-020-10143-7

R Core Team. (2022). *R: A Language and Environment for Statistical Computing* (Version 4.1.3) [Computer software]. R Foundation for Statistical Computing. https://www.R-project.org/

Reguera-Alvarado, N., Blanco-Oliver, A., & Martín-Ruiz, D. (2016). Testing the predictive power of PLS through cross-validation in banking. *Journal of Business Research*, *69*(10), 4685–4693. https://doi.org/10.1016/j.jbusres.2016.04.016

Ricketts, E. J., Snorrason, Í., Kircanski, K., Alexander, J. R., Thamrin, H., Flessner, C. A., Franklin, M. E., Piacentini, J., & Woods, D. W. (2018). A latent profile analysis of age of onset in pathological skin picking. *Comprehensive Psychiatry*, *87*, 46–52. https://doi.org/10.1016/j.comppsych.2018.08.011

Rojas-Méndez, J. I., Parasuraman, A., & Papadopoulos, N. (2017). Demographics, attitudes, and technology readiness. *Marketing Intelligence & Planning*, *35*(1), 18–39. https://doi.org/10.1108/MIP-08-2015-0163

Rosenberg, J. M., Beymer, P. N., Anderson, D. J., Van Lissa, C. J., & Schmidt, J. A. (2018). tidyLPA: An R Package to Easily Carry Out Latent Profile Analysis (LPA) Using Open-Source or Commercial Software. *Journal of Open Source Software*, *3*(30), 978. https://doi.org/10.21105/joss.00978

Rotter, J. B. (1966). Generalized expectancies for internal versus external control of reinforcement. *Psychological Monographs: General and Applied*, *80*(1), 1–28. https://doi.org/10.1037/h0092976

Sankeerthana, G., & Raghuram Kadali, B. (2022). A strategic review approach on adoption of autonomous vehicles and its risk perception by road users. *Innovative Infrastructure Solutions*, *7*(6), 1–29. https://doi.org/10.1007/s41062-022-00951-4

Sharma, I., & Mishra, S. (2022). Ranking preferences towards adopting autonomous vehicles based on peer inputs and advertisements. *Transportation*, 1–54. https://doi.org/10.1007/s11116-022-10304-w

Shrestha, B. P., Millonig, A., Hounsell, N. B., & McDonald, M. (2017). Review of Public Transport Needs of Older People in European Context. *Journal of Population Ageing*, *10*(4), 343–361. https://doi.org/10.1007/s12062-016-9168-9

Spurk, D., Hirschi, A., Wang, M., Valero, D., & Kauffeld, S. (2020). Latent profile analysis: A review and "how to" guide of its application within vocational behavior research. *Journal of Vocational Behavior*, *120*, 103445. https://doi.org/10.1016/j.jvb.2020.103445

Steyerberg, E. W., Harrell, F. E., Borsboom, G. J., Eijkemans, M. J., Vergouwe, Y., & Habbema, J. D. (2001). Internal validation of predictive models: Efficiency of some procedures for logistic regression analysis. *Journal of Clinical Epidemiology*, *54*(8), 774–781. https://doi.org/10.1016/S0895-4356(01)00341-9

Takayama, L., Marder-Eppstein, E., Harris, H., & Beer, J. M. (2011). Assisted driving of a mobile remote presence system: System design and controlled user evaluation. In A. Bicchi (Ed.), *2011 IEEE International Conference on Robotics and Automation: (ICRA 2011) ; Shanghai, China, 9 - 13 May 2011* (pp. 1883–1889). IEEE. https://doi.org/10.1109/ICRA.2011.5979637

Tein, J.-Y., Coxe, S., & Cham, H. (2013). Statistical Power to Detect the Correct Number of Classes in Latent Profile Analysis. *Structural Equation Modeling: A Multidisciplinary Journal*, *20*(4), 640–657. https://doi.org/10.1080/10705511.2013.824781

Trapani, J., & Hale, K. (2019). Higher Education in Science and Engineering. Science & Engineering Indicators 2020. Nsb-2019-7. *National Science Foundation*. https://eric.ed.gov/?id=ED599398

van der Laan, J. D., Heino, A., & Waard, D. de (1997). A simple procedure for the assessment of acceptance of advanced transport telematics. *Transportation Research Part C: Emerging Technologies*, *5*(1), 1–10. https://doi.org/10.1016/s0968-090x(96)00025-3

Venkatesh, V. (2000). Determinants of Perceived Ease of Use: Integrating Control, Intrinsic Motivation, and Emotion into the Technology Acceptance Model. *Information Systems Research*, *11*(4), 342–365. https://doi.org/10.1287/isre.11.4.342.11872

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. *MIS Quarterly*, *36*(1), 157. https://doi.org/10.2307/41410412

Wiggins, B. C. (2000). *Detecting and Dealing with Outliers in Univariate and Multivariate Contexts*. https://eric.ed.gov/?id=ED448189

Wong, T.-T., & Yeh, P.-Y. (2020). Reliable Accuracy Estimates from k -Fold Cross Validation. *IEEE Transactions on Knowledge and Data Engineering*, *32*(8), 1586–1594. https://doi.org/10.1109/TKDE.2019.2912815

Woo, S. E., Jebb, A. T., Tay, L., & Parrigon, S. (2018). Putting the “Person” in the Center. *Organizational Research Methods*, *21*(4), 814–845. https://doi.org/10.1177/1094428117752467

Xu, Z., Zhang, K., Min, H., Wang, Z., Zhao, X., & Liu, P. (2018). What drives people to accept automated vehicles? Findings from a field experiment. *Transportation Research Part C: Emerging Technologies*, *95*, 320–334. https://doi.org/10.1016/j.trc.2018.07.024

Yu, H., Tak, S., Park, M., & Yeo, H. (2019). Impact of Autonomous-Vehicle-Only Lanes in Mixed Traffic Conditions. *Transportation Research Record: Journal of the Transportation Research Board*, *2673*(9), 430–439. https://doi.org/10.1177/0361198119847475

Yuen, K. F., Choo, L. Q., Li, X., Wong, Y. D., Ma, F., & Wang, X [Xueqin] (2022). A theoretical investigation of user acceptance of autonomous public transport. *Transportation*, 1–25. https://doi.org/10.1007/s11116-021-10253-w

Zhang, T., Da Tao, Qu, X., Zhang, X., Zeng, J., Zhu, H [Haoyu], & Zhu, H [Han] (2020). Automated vehicle acceptance in China: Social influence and initial trust are key determinants. *Transportation Research Part C: Emerging Technologies*, *112*, 220–233. https://doi.org/10.1016/j.trc.2020.01.027

Tables

Table 1 Sample characteristics based on gender

Characteristics	Total (N = 388)	Male (n = 111)	Female (n = 276)	Divers (n = 1)
Average Age (SD)	26.19 (7.25)	26.67 (6.05)	26.02 (6.69)	22.00 (0.00)
Training (%)				
No degree	1 (0.3 %)	1 (0.9 %)	-	
High School Diploma, i.e., German Mittelschulabschluss [a]	1 (0.3 %)	-	1 (0.4 %)	
High School Diploma, i.e., German Realschulabschluss[a]	13 (3.4 %)	6 (5.4 %)	7 (2.5 %)	
University of applied sciences entrance qualification, i.e., German Fachhochschulreife	49 (12.6 %)	17 (15.3 %)	32 (11.6 %)	
University entrance qualification, i.e., German Abitur	274 (70.6 %)	76 (68.5 %)	197 (71.4 %)	1 (100 %)
Academic degree, i.e., bachelor, master or higher	19 (4.9 %)	3 (2.7 %)	16 (5.8 %)	
No answer	22 (5.7 %)	5 (4.5 %)	17 (6.2 %)	
Annual income (%)	9 (2.3 %)	3 (2.7 %)	6 (2.2 %)	
< 20 000 €				
20 000 € – 30 000 €	124 (32.0 %)	22 (19.8 %)	101 (36.6 %)	1 (100 %)
30 000 € – 40 000 €	80 (20.6 %)	25 (22.5 %)	55 (19.9 %)	
40 000 € – 50 000 €	71 (18.3 %)	27 (24.3 %)	44 (15.9 %)	
50 000 € – 60 000 €	37 (9.5 %)	14 (12.6 %)	23 (8.3 %)	
> 60 000 €	17 (4.4 %)	7 (6.3 %)	10 (3.6 %)	
No answer	13 (3.4 %)	5 (4.5 %)	8 (2.9 %)	

Note. [a] The terms correspond to German school diplomas. Mittelschulabschluss and Realschulabschluss are equivalent to a High School diploma after nine and ten years

Table 2 Used constructs and inventories with item characteristics, Cronbach's Alpha and source

Construct / Inventory	Item Count	Range	α	Source	Example Item
Age	1				
Neuroticism	6	1 (strongly disagree) to 5 (strongly agree)	.84	NEO-FFI-30, Körner et al., 2008	I often feel tense and nervous.
Extraversion	6		.75		I am a cheerful, good-humoured person.
Openness	6		.80		I often enjoy playing with theories or abstract ideas.
Agreeableness	6		.70		I always try to act considerate and sensitively.
Conscientiousness	6		.78		I keep my things neat and clean.
Self-efficacy	3		.85	Allgemeine Selbstwirksamkeits kurzskala (ASKU), Beierlein et al., 2012	I can cope well with most problems by my own efforts.
Internal Control Belief	3		.62	Jakoby & Jacob, 1999	I like to take responsibility.
External Control Belief	3		.47		Success often depends less on performance and more on luck.
Trait Anxiety	3	1 (strongly disagree) to 7 (strongly agree)	.78	Skalen zur Messung manifester Angst (MAS); Lück & Timaeus, 1969	I am almost always afraid of something or someone.
Disposition to Trust	6		.91	Gefen & Straub, 2004	I generally trust other people.
Technology Acceptance	4		.92	Kurzskala Technikbereitschaft, Neyer et al., 2012	I am very curious about new technical developments.
Technology Competence	4		.91		When dealing with modern technology, I am often afraid of failing.
Technology Control Belief	4		.81		Whether I am successful in using modern technology depends mainly on me.
Technology Anxiety	3		.63	Based on Venkatesh, 2000	New technology doesn't scare me at all.
Trust in Technology	2		.81	Based on Jian et al., 2000	I trust new technologies.
Intention to Use	1			Self-developed based on Venkatesh et al., 2012	I plan to use autonomous shuttles like the People Mover in the future if they were available to me.

Note. α: Cronbach´s Alpha

Table 4 Fit indices of the different LPA profile solutions for the training and test data set

Record	Model	AIC	BIC	saBIC	LMR	Entropy	Smallest profile (%)
Training	1	14260	14380	14278	-	1	1
(*n* = 313)	2	13751	13934	13779	514.17**	.79	45.0
	3	13624	13871	13662	151.23**	.80	21.4
	4	13515	13826	13562	136.11**	.83	11.5
	5	13368	13743	13426	170.13**	.86	4.5
Test	1	3453	3528	3427	-	1	1
(*n* = 75)	2	3364	3477	3323	115.19**	.84	.37
	3	3319	3472	3264	74.31**	.95	.16
	4	3328	3520	3259	22.29**	.89	.13
	5	3297	3529	3213	61.31**	.89	.04

Note. *N* = 388; LPA = Latent Profile Analysis; AIC = Akaike's Information Criterion; BIC = Bayesian Information Criterion; saBIC = adjusted BIC; LMR = Lo Mendell Rubin Likelihood Ratio Test;

** *p*-Value < .01

Figures

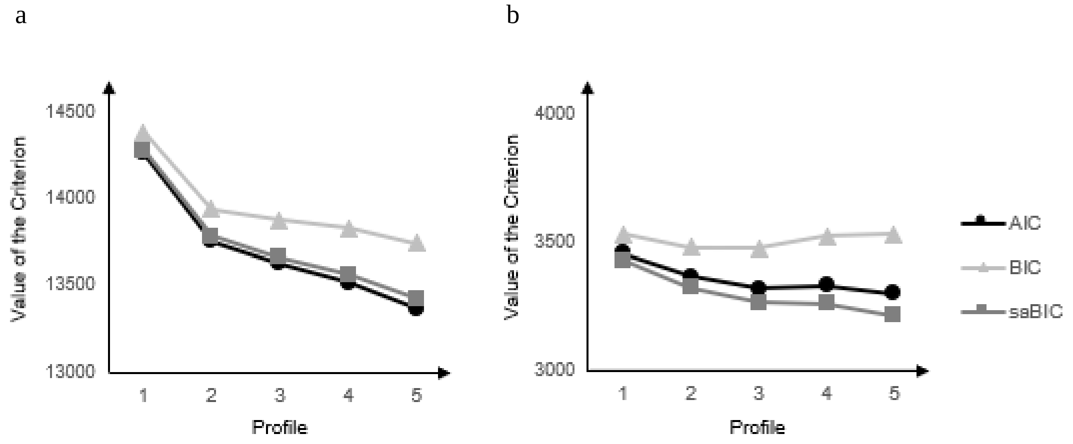

Fig. 1 Elbow plot for fit indices across the profile solutions for training analysis (a) and test analysis (b)

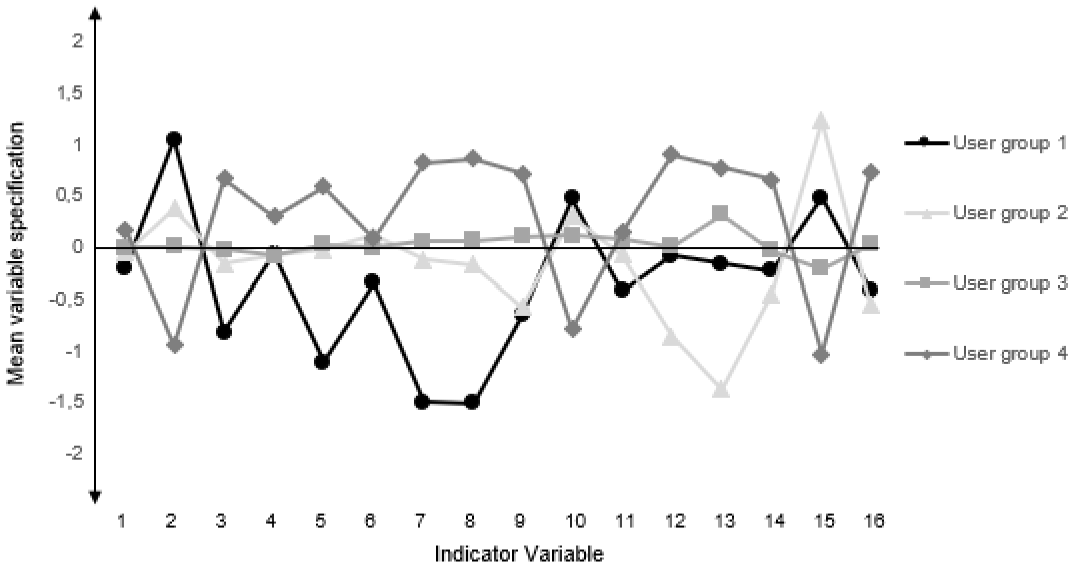

Fig. 2 Response patterns of the four user group profiles showing differences across the z-standardized indices

Note. N = 315; Profile 1: n = 66, Profile 2: n = 36, Profile 3: n = 66, Profile 4: n = 145; 1 = Age, 2 = Neuroticism, 3 = Extraversion, 4 = Openness, 5 = Conscientiousness, 6 = Agreeableness, 7 = Self-efficacy, 8 = Internal Control Belief, 9 = External Control Belief, 10 = Trait Anxiety, 11 = Disposition of Trust, 12 = Technology Acceptance, 13 = Technology Competence, 14 = Technology Control Belief, 15 = Technology Anxiety, 16 = Trust in Technology

Table 3 *Correlations of the central variables studied*

Variable	*M*	*SD*	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.
1. Gender	0.72	0.47																	
2. Age	26.19	7.25	-.05																
3. ITU	5.14	1.28	-.12	.02															
4. Neuroticism	1.63	0.79	.24**	-.14**	-.14**														
5. Extraversion	2.69	0.61	.01	.04	.19**	-.33**													
6. Openess	2.43	0.75	.05	.05	.13**	-.04	.09												
7. Agreeableness	2.88	0.62	.24**	-.03	.00	-.09	.10*	.02											
8. Conscientiousnes	3.23	0.55	.14**	-.02	.08	-.25**	.22**	.03	.24**										
9. Self Efficacy	3.96	0.58	-.07	.05	.17**	-.37**	.30**	.18**	.02	.42**									
10. Internal Control Belief	3.84	0.62	.15**	-.02	.00	.01	.02	-.07	.03	-.02	.-.01								
11. External Control Belief	3.39	0.64	-.04	.03	.10*	-.03	-.02	.04	-.02	-.04	.05	.25**							
12. Trait Anxiety	4.10	1.36	.26**	-.21**	-.11*	.61**	-.20**	-.05	.07	-.01	-.20**	.04	-.03						
13. Disposition to Trust	4.50	1.09	.07	.01	.11*	-.10	.30**	-.00	.27**	.08	.10*	.05	-.02	-.10					
14. Technology Acceptance	4.59	1.43	-.12**	-.01	.25**	-.17**	.24**	.08	-.10*	.07**	.22**	.03	.09	-.11*	.05				
15. Technology Competence	5.78	1.09	-.13**	-.09	.19**	-.27**	.10	.04	.14**	.16**	.19**	.01	.05	-.19**	-.01	.35**			
16. Technology Control Belief	5.22	0.95	-.11*	-.05	.20**	-.12‘	.06	.07	.02	.12**	.24**	-.01	.02	-.07	.10	.29**	.29**		
17. Technology Anxiety	2.64	0.99	.14**	.02	-.30**	.28**	-.22**	-.02	-.06	-.16**	-.26**	-.01	-.02	.22**	-.07**	-.54**	-.63**	-.39**	
18. Trust in Technology	5.02	1.04	.03	-.01	.36**	-.11*	.16**	.01	.05	.11**	.18**	09	.11*	-.14**	.33**	.40**	.16**	.26**	-.41**

Note. N = 388;

* p < .05;

** p < .01