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# Predicting acceptance of autonomous shuttle buses by personality profiles: a latent profile analysis

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## 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, potential users are 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 potential user and the needs of the potential user groups to marketing them effectively. Our study, therefore, addressed the identification of personality profiles for potential users 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 personality profiles that differed significantly from each other in their willingness to use AVs. In total, potential users with lower anxiety and increased self-confidence were more open toward AVs. Technology affinity as a trait also contributes to the differentiation of potential user profiles 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

## 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

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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 potential user 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 profiles for potential users of autonomous vehicles (AV) based on selected personal characteristics and dispositions.

## Literature review and research framework

The characteristic of the potential 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), region of living (Lemonnier et al. 2020), 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 and 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 and Raghuram Kadali 2022). In addition, relevant differences in AV acceptance also emerge in relation to region of living. Thus, individuals from urban regions are more likely to adopt AVs than individuals from rural regions (Deb et al. 2017). This is plausible in that people in urban regions may be less likely to own a car or parking may be more difficult in cities (Nielsen and Haustein 2018; Nordhoff et al. 2018a). Therefore, AVs may appear attractive especially for people who have their center of living in a city. 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 and 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 agreeable users showed more concern in this regard, e.g., regarding the reliability and usability of AVs (Charness et al. 2018; 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 and 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 and 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 and Blecker 2017). In addition, technology affinity contributes positively to trust in new technologies, which in turn lowers perceptions of potential risks (Choi and 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 and 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. Keszei (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 potential 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 types of potential users 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 characteristics of potential users and thus identify profiles. These profiles can present the complex set of characteristics and needs of potential users 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 profile 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 profiles 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, to identify and exploratively analyze profiles of potential AV users with respect to the ITU AVs. Personality, in particular, which also proved to be crucial for the acceptance of AVs in our research, is widely used for the identification of person profiles within a society (e.g., Perera and McIlveen 2017; Rzeszutek and Gruszczyńska 2020). Due to its relative stability, it allows reliable and consistent predictions of distal outcomes, as in our case of ITU (Diener and Lucas 2019). Therefore, the analysis is based on variables 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 personality profiles based on which to examine the ITU of potential AV users?
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 platforms of universities, social media, and personal approach. Therefore, when we refer to bus users in our study context, we always refer to potential users, since the data were collected online and independently of actual bus use. At the same time, this allows us to identify groups of people who are less willing to use AVs. To provide the participants with a vivid and detailed idea of the ride in an autonomous bus 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

**Table 1** Sample characteristics based on gender

Characteristics	Total ( <i>N</i> = 388)	Male ( <i>n</i> = 111)	Female ( <i>n</i> = 276)	Divers ( <i>n</i> = 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 <sup>a</sup>	1 (0.3%)	–	1 (0.4%)	
High School Diploma, i.e., German Realschulabschluss <sup>a</sup>	13 (3.4%)	6 (5.4%)	7 (2.5%)	
University of applied sciences entrance qualifi- cation, 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 (%)				
< 20 000 €	9 (2.3%)	3 (2.7%)	6 (2.2%)	
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%)	

<sup>a</sup>The terms correspond to German school diplomas. Mittelschulabschluss and Realschulabschluss are equivalent to a High School diploma after nine and ten years

credit for participation (students must take part in studies and experiments carried out by researchers of the universities).

## Instrument and profile indices

Based on the current state of research, we selected 16 variables as possible indices for personality profiles by which the ITU is to be predicted: 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 characteristics of potential users. This combination should later enable us to place the ITU of potential customers on AVs in the context of individual personality characteristics. The questionnaires and instruments used are shown in Table 2. A detailed overview of all items and scales used in the study is available in the OSF repository, <https://osf.io/87vr4/>. 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. 2018b), 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).

## 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 min 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/>.

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

Construct/inventory	Item count	Range	$\alpha$	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 Selbstwirksamkeitskurzsкала (ASKU), Beterlein 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 manifesten Angst (MAS); Lück and Timaeus, (1969)	I am almost always afraid of something or someone
Disposition to Trust	6		.91	Gefen and Straub (2004)	I generally trust other people
Technology Acceptance	4		.92	Kurzsкала 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.  $\alpha$ : Cronbach's Alpha



## 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. In contrast to factor or regression analytic methods, LPA focuses on relationships between individuals rather than relationships between variables (Bauer and Curran 2004). This enables the probabilistic assignment of each potential user to the profile with the best fit based on the individual response pattern (Tein et al. 2013). Thus, LPA provides a differentiated insight into profile-specific characteristics within a diverse network of variables. The method is therefore particularly well suited for our goal of identifying and distinguishing personality profiles of potential users (Howard and Hoffman 2018; Woo et al. 2018). The approach allows a subsequent description of various empirically determined personality profiles in relation to the ITU. Our study thus contributes to mapping the knowledge about the characteristic of potential 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 and 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 Criteria (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 and 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 0.80 being considered very

separable (Araújo et al. 2018; Celeux and 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 and Soromenho 1996; Clark and 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 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, region of living, 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 (1–4) to the identified profiles.

To test the predictive validity of the personality profiles found in relation to the ITU, a regression under tenfold 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 tenfold cross-validation in both data sets. The tenfold 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 and Yeh 2020). In this way, we performed a regression with the independent variable profile 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 4 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 3 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 and 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 0.80 as a measure of classification confidence only for the four- and five-profile solutions above which it is classified as highly discriminative (Celeux and Soromenho 1996; Muthén 2008; Tein et al. 2013). Our goal to identify personality profiles of potential users 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 0.80 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

**Table 3** 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 ( <i>n</i> = 313)	1	14,260	14,380	14,278	—	1	1
	2	13,751	13,934	13,779	514.17**	.79	45.0
	3	13,624	13,871	13,662	151.23**	.80	21.4
	4	13,515	13,826	13,562	136.11**	.83	11.5
	5	13,368	13,743	13,426	170.13**	.86	4.5
Test ( <i>n</i> = 75)	1	3453	3528	3427	—	1	1
	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

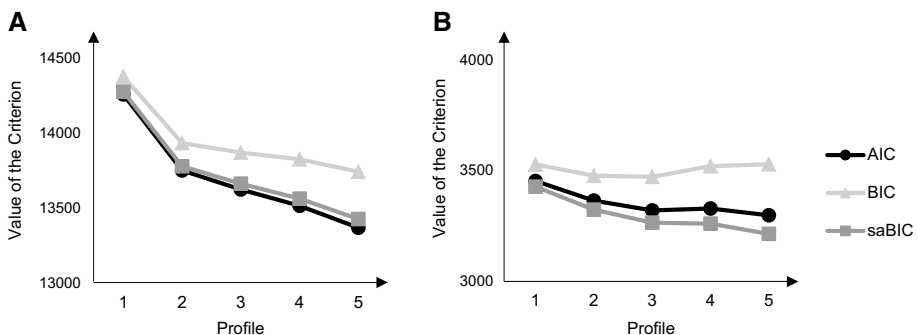
*N* = 388; LPA latent profile analysis, AIC Akaike's information criterion, BIC Bayesian information criterion, saBIC adjusted BIC, LMR Lo Mendell Rubin likelihood ratio test

\*\**p* value < .01

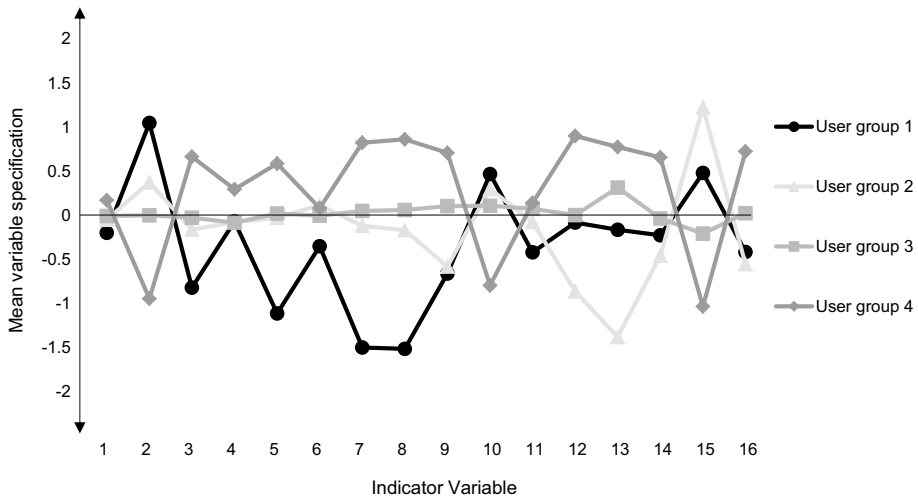
solution. With the aforementioned limitations regarding the information criteria, our profile decision thus proved to be replicable and valid.

### 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. Figure 2 provides an overview of the mean variable expressions of the four different profiles. 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.



**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 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

Profile 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 most likely to be assigned to profile 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. The group with profile 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. This is consistent with the fact that the proportion of individuals from urban regions was the highest (80.56%).

Profile 2 ( $n=66$ ) was also characterized by increased anxiety-related scores. Unlike profile 1, neuroticism and trait anxiety were less pronounced. Rather, this profile 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 most likely to be classified to profile 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%). Individuals most probably to be assigned to profile 2 also reported the highest level of acceptance of using public transportation compared to the other profiles ( $M=4.22$ ,  $SD=1.73$ ). They showed the largest proportion of people from rural areas (31.82%).

The response pattern of profile 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 of individuals most probably to be associated with profile 3 was also close to the sample average with  $M=26.26$  ( $SD=7.16$ ). Further analyses revealed that this group enjoyed public transportation use the least compared to the other profiles ( $M=3.52$ ,  $SD=1.74$ ).

Profile 4 ( $n=66$ ) showed a response pattern that was opposite in its characteristics to the pattern of profile 1. It was noticeably less anxious. A particularly noteworthy difference was the strikingly low technology anxiety and high technology affinity of profile 4, which clearly distinguished it from the first two profiles. This corresponded with increased openness to change, extraversion and conscientiousness. In addition, self-efficacy and internal and external control beliefs were higher in this profile. The group of individuals who are most likely to be classified to profile 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 with this profile were more likely to own a driver's license (95.45%) and own a car (77.27%) compared to other profiles.

### 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,  $F(3, 249)=7.36$ ,  $p<0.001$ ,  $R^2=0.08$ .

Compared to profile 1, individuals most likely to be assigned to profile 2 had a 0.33 lower ITU,  $t(249)=-1.15$ ,  $p=0.252$ , and individuals most likely to be assigned to profile 3 had a 0.18 higher ITU,  $t(249)=0.69$ ,  $p=0.492$ , although the differences were not significant. For profile 4, ITU was significantly higher by 0.78,  $t(249)=2.75$ ,  $p=0.001$ . The ITU of individuals who are most probably to be classified to profile 2 was again significantly different from the ITU of individuals considered most likely to belong to profile 3,  $b=0.51$ ,  $t(249)=2.46$ ,  $p=0.015$ , and from the ITU of individuals considered most likely to be assigned to profile 4,  $b=1.12$ ,  $t(249)=4.61$ ,  $p<0.001$ . The difference between profile 3 and 4 was also significant, with the ITU for profile 3 being 0.61 lower,  $t(249)=-2.98$ ,  $p=0.003$ . Thus, profile 4 showed the highest ITU, followed by profiles 3 and 1. Persons most likely to be assigned to profile 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 (James et al. 2021).

## Discussion

### Summary and practical implications

Our study aimed to identify personality profiles 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 personality profiles as comprehensively as possible. 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 profiles. Second, we tested these profiles directly for their predictive power for AVs' ITU to ensure their practical relevance. As a result, our profiles 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 personality profiles 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 potential user belongs. The profiles 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 profiles that differed in their personality characteristics and their ITU. Particularly important indices of profile affiliation were the variables of self-confidence (i.e., self-efficacy, internal and external control belief), general anxiety (i.e., neuroticism, trait anxiety, and technology 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 most probably to be assigned to profile 1 were characterized by a high level of general anxiety and insecurity, with a slightly below-average affinity for technology and increased technology anxiety. 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 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, perhaps due to general anxiety, people who are most likely to be classified to profile 1 may be more likely to avoid AV use. It is interesting to note that profile 1, which in our study was associated with the proportionally lowest car and driver's license ownership, was associated with a comparatively low ITU of autonomous buses. This link is surprising because it could be expected that people with reduced possibilities for private mobility are more likely to use public transport services such as autonomous shuttle buses. It is possible that people most likely to be associated with profile 1 are less familiar with autonomous driving assistance systems (e.g., parking assistant in private cars) due to lower car use and are therefore also more skeptical of the autonomous technology. 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 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 profile 1, profile 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 profile 1). It is possible that individuals most probably to be classified to



profile 1 and 2 attributed less control to the external AI technology than to themselves and were therefore less convinced of AVs. To give potential 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 potential users who are most likely to be associated with profile 2. Manufacturers could provide training to help users to better understand AVs and reduce potential technology anxiety. Compared to the profile 1 group, 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 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 profile 3, a relatively average response pattern emerged across the variables, with slightly increased technology competence and slightly decreased technology anxiety. People who are most probably to be classified to profile 3 showed an average ITU, although they 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, people who are most likely to be classified to profile 3 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.

Profile 4 differed from profile 1 in almost all variables. People most likely to be associated this profile are characterized by pronounced self-confidence, low anxiety, and a high affinity for technology in every respect. It seems plausible that members of profile 4, i.e., people who are more likely to have higher self-confidence on average attribute better coping skills to themselves and are less anxious. As a result, they may be more open to new technology. Accordingly, this profile group was most likely to use AVs. Complementary to profile 1, which had a comparatively low ITU with the lowest proportion of car and driver's license owners, we found the highest ITU for profile 4 with the highest proportion of car and driver's license owners. It is possible that people most likely to be assigned to profile 4 (in line with our rationale for profile 1) have more experience with autonomous driving assistance systems and are therefore more open to autonomous driving. Another explanation for the comparatively high ITU may be that people most likely to be associated with profile 4 had on average the highest income and thus have better access to (often expensive) new technologies or are more familiar with them (Gallo et al. 2022; Yuen et al. 2022). Given their high extraversion and openness, persons with profile 4 could be further encouraged to use AVs by highlighting social and sustainable aspects of autonomous ride-sharing services. With their openness to technologies and AVs, this 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, individuals who are most likely to be assigned to profile 4 could be suitable



for introducing skeptical target groups, such as people who are most probably associated with profiles 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.

It is noteworthy that our profiles, taken individually and also in their overall constellation, provide a thoroughly consistent, coherent picture. The characteristic response patterns of the single profiles follow a logical, reasonable constellation, e.g., for the positive association between anxiety- and insecurity-related variables. Overall, the four profiles form a holistic pattern in that they complement each other in a meaningful way and can be clearly differentiated from each other. Thus, our profiles are not only plausible in their respective logic, but they also complement each other to form a comprehensive overall concept. Overall, the four profiles showed a very heterogeneous pattern of characteristics and willingness to use AVs. Specially for profiles 1 and 2, anxiety was still associated with a low ITU. These results are a 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 most likely to be associated with profile 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 profile 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 analysis of potential users, 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. Particularly due to the limited age variance, our profiles show relatively homogeneous age structures. This made it difficult for us to interpret the profiles in terms of age differences. We were therefore not able to address differences, e.g., in technology affinity, which may have been caused by age (Blut and Wang 2020). To further deepen the research on profiles of potential AV users, the profiles should be considered in future studies in samples with greater age variance. 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). In addition, several studies showed that different cultures differ in their AV acceptance. For example, Asian areas show higher acceptance of AVs than European areas, possibly due to a higher willingness to accept circumstances (e.g., AV adoption), especially if they benefit society (Potoglou et al. 2020; Yun et al. 2021). 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, data was collected online regardless of whether individuals had prior experience with autonomous buses. This enabled us to also survey individuals who would not use autonomous buses and to assess them in terms of their personalities. However, our study thus refers exclusively to potential and not actual users. This must be taken into account when interpreting the results. As soon as autonomous buses are available on a large scale, this study should be conducted with actual users. To provide the participants with an impression of driving an autonomous bus that is as close to reality as possible, 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) and ensures an equal experience base across all participants (Kettle and Lee 2022). 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 of the LPA represent probabilities and not absolute values. Our class assignments are highly likely to apply, but LPA does not guarantee the correctness of our solutions. LPA enabled us as a procedure to initially simplify complex personality dimensions by forming profiles to derive practical implications for the introduction of AVs. However, it must also be noted that this procedure entails a loss of information in two aspects: First, in order to perform the regression, it was important to assign each subject to the profile to which he or she belongs with the highest probability based on the personality pattern (Clark and Muthén 2009). However, the profile assignment means that this probability no longer can be taken into account in the subsequent regression. For example, if a person has a probability of 0.55 of belonging to Profile 3, he or she will be assigned to that profile in the same way as a person whose probability of belonging to Profile 3 is 1.00. In the subsequent regression, both persons are counted identically as belonging to profile 3, regardless of what the original assignment probability was (Clark and Muthén 2009). Second, profile affiliation represents a simplification of a previously more complex response pattern. In the regression, we deliberately left the level of personality variables and only considered profile affiliation to meet our demand for complexity reduction. The pure profile affiliation does not reveal the extent to which the respective personality variables influence the ITU. However, this was not the goal of the study because the associations of the selected personality variables with ITU have already been investigated in previous research. Since the specific associations between the personality variables and ITU can be interesting for the interpretation of the results, we have provided a correlation matrix in Table 4 in the appendix, from which the associations between the examined constructs can be seen. In this context, we would also like to point out that profile affiliation was indeed predictive of ITU in our study. However, as in any regression, these trends are not exempt from variation. Thus, when we assign an individual to the profile to which he or she is most likely to belong based on his or her response pattern, our results allow us to make predictions but not absolute statements about expected ITU. Regarding the model decision, it must be noted that most of 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 and 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 the previous findings and integrated them by identifying four profiles based on the most relevant personality traits and related them to the ITU AVs. Our results allow us to draw implications about the characteristics of four profiles of potential users and how to respond to them. These identified profiles differed particularly in variables of self-confidence (i.e., self-efficacy, internal and external control belief), general anxiety (i.e., neuroticism, trait anxiety and technology anxiety), and affinity for technology (i.e., technology acceptance, competence, and control belief): Profiles 1 and 2 were characterized by low technology affinity and ITU, which was accompanied by high general anxiety and uncertainty in profile 1, and high technology anxiety in profile 2. Profile 3 showed average values across all variables, including for the ITU. With high self-confidence and affinity for technology accompanied by low anxiety, profile 4 proved to be particularly promising for the intention to use AVs and thus differed considerably from the other three profiles. Manufacturers and transit agencies should take the differences into account in their AV marketing strategies. In particular, people with a low affinity for technology (mainly represented in profile 2), but also with general anxiety (mainly represented in profile 1), should be approached with special consideration in order to increase their ITU systematically. Complementary to this, people who are particularly affine to technology and have low levels of anxiety (mainly represented in profile 4) can be deliberately targeted to serve as multipliers for the idea of autonomous driving. An implementation concept tailored to the profiles can help to meet the individual needs of each of the four profile groups. In summary, our study provides important contributions from a psychological perspective to better define potential AV users in terms of their characteristics and potential needs. Our implications provide initial suggestions on how the different profiles and needs of potential users can be addressed by manufacturers and providers. Future research should follow up on this and examine in more detail how potential users can be approached depending on their personality profile.

## Appendix

See Table 4.

**Table 4** Correlations of the central variables studied

Variable	<i>M</i>	<i>SD</i>	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. Openness	2.43	0.75	.05	.05	.13**	-.04	.09												
7. Agreeableness	2.88	0.62	.24**	-.03	.00	-.09	.10*	.02											
8. Conscientiousness	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**

*N* = 388\**p* < 0.05\*\**p* < 0.01

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

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## Declarations

**Conflict of interest** All authors declare that they have no conflicts of interest.

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