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Simplifying acceptance: A general acceptance factor predicting intentions to use shared autonomous vehicles

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ABSTRACT

The primary aim of this study was to develop an accurate measure of acceptance for shared autonomous vehicles (SAVs) and to assess whether this measure can predict intentions to use SAVs. One leading model for explaining technology uptake is the UTAUT (Unified theory of acceptance and use of technology). This model is extensive and has received numerous suggested extensions and revisions, even being developed into a Multi-Level Model of Autonomous Vehicle Acceptance (MAVA). The challenge is to consolidate a model that effectively measures SAV acceptance and to determine which extensions capture the unique social situation within SAVs.

The current study used survey data from 1902 respondents. The sample was split into two: one half underwent a principal component analysis (PCA) and the other half a confirmatory factor analysis (CFA). We found that the 24 items we included were reducible to a single general acceptance factor (GAF), with three additional factors measuring interpersonal security, sociability, and attractivity. The GAF was, by a large margin, the most efficacious predictor of intention to use SAVs. The GAF could be further reduced to as little as two predictors, trust and usefulness, accounting for over 70 % of the variance in intention to use. However, there is also an argument to be made that the other components of SAV acceptance may capture different nuances of the service, particularly relating to the social situation. Interaction terms show differences between genders in their rating of sociability and how this impacts intentions to use SAVs.

Our findings carry significant implications for future research in this field. They underscore the pivotal roles of trust and usefulness while corroborating the notion that SAV acceptance is best represented by a single latent component. However, further investigation is warranted to explore individual-level moderating effects on the other components, potentially offering novel insights for the design of future SAV services.

1. Introduction

Automated vehicles (AVs) represent a technological breakthrough that could revolutionize transport in the coming years. However, their widespread adoption is contingent on the degree to which people accept and use this new mode of transportation. The potential benefits of automated vehicles, such as increased safety and reduced traffic congestion, are well-documented (Hult et al., 2016; Iclodean et al., 2020; Jones & Leibowicz, 2019). Shared autonomous vehicles (SAVs) is one of the denominations of the application of

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AV technology into the public transport system. This may take the form of smaller robo-taxis that offer autonomous ridesharing services. Simulated scenarios show how the adoption of privately owned AVs may exacerbate current congestion, overloading the existing infrastructure systems (COWI, 2019; PTV Group, 2015). Wide acceptance of AVs in the public transport sector is key to achieve the promised goals of AV technology and avoid congestion. To best achieve public acceptance, we need social science to accompany the technological innovations. Only very recently has there been increased attention given to psychological aspects of introducing autonomous vehicles into the transport system (Azad et al., 2019; Cohen et al., 2020). Thus, research on the use of SAVs in a public transport context is sparse (Mouratidis & Serrano, 2021). Acceptability is often used interchangeably with intention to use a technology, although differences in definitions across the technology acceptance lifecycle have been noted (Nadal et al., 2020). While numerous factors are recognized as crucial for public acceptance of AVs, research on developing a streamlined measurement approach remains scant. Existing models are often comprehensive and necessitate contextual adjustments (Nordhoff et al., 2019; Venkatesh et al., 2003). There is little research investigating how these models adapt to the novel social situation that arises within small, stewardless SAVs.

This study aims to refine the conceptualization and measurement of SAV acceptance, and to delineate how it diverges from traditional AV acceptance. First, we will review literature on factors predicting AV acceptance and explore which extensions capture the novelty of the social situation within SAVs. Second, we will present our study's methods and results. Here, we apply dimension reduction techniques and test different models of prediction. Finally, we will discuss our findings and their applications for future research and measurement of SAV acceptance.

1.1. Literature review

Over the past decades, research has explored numerous variables that influence acceptance and use of technology. Many models have evolved from the foundational technology acceptance model (TAM) by incorporating additional factors such as trust and perceived risk (Davis, 1986; Zhang et al., 2019). One particularly popular approach has been the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2016). This theory originated two decades ago by integrating eight different theories aimed at understanding technology acceptance (Venkatesh et al., 2003). These eight theories were the theory of reasoned action, theory of planned behavior, technology acceptance model, motivational model, a combined version of TAM and TPB, model of PC utilization, innovation diffusion theory, and the social cognitive model. The UTAUT has since gone through several iterations and additions, partly in response to research extending the model into new fields of study (Blut et al., 2022; Venkatesh et al., 2016). It remains an important point that the model should seek to contextualize and add specifics to the model depending on the field of research.

UTAUT's success is notable, but its complexity reduces parsimony. Researchers have attempted to adapt parts of the model for AV acceptance, indicating varying impacts on behavioral intentions and actual behaviors (Bala et al., 2023; Korkmaz et al., 2021; Madigan et al., 2017; Nordhoff et al., 2019). While oft-cited and widely successful, the UTAUT has been found to have some variance in effect on behavioral intention depending on the context, and also weaker effects on actual behavior than on behavioral intention (Blut et al., 2022). This suggests that there is still work to be done in adapting the model to acceptance of SAVs.

UTAUT has been adapted to the realm of AV acceptance (Nordhoff et al., 2019). The Multi-Level Model of Automated Vehicle Acceptance (MAVA), draws on insight from 124 previous studies on AV acceptance (Nordhoff et al., 2019). Like the UTAUT, the model is vast, and questions remain about how well research regarding AVs in general fit the context of vehicles introduced in the public transport system. There are unanswered questions about the novel social situations that arise in small, shared vehicles, particularly when the bus driver (steward) is removed (Sovacool & Axsen, 2018). Additionally, the prospect of mobility as a service (Maas), where SAVs pick you up wherever, instead of traditional bus stops, can further exacerbate the intimate feeling of such vehicles. A recently developed extension of the UTAUT, called the UTAUT4-AV, finds that it predicts around 90 % of variance in intentions to use autonomous cars, robo-taxis, and autonomous air mobility vehicles (Bellet & Banet, 2023). This recent specification also includes satisfaction with current mode of transport.

Discovering the most precise way of measuring and conceptualizing MAVA-constructs can allow inclusion of other factors that may be specific to acceptance of SAVs. These factors could include the social situation, privacy concerns, or the trust in public transport providers. Passengers' social preferences may be more salient in small SAVs, particularly if they can pay to ride alone. Research has suggested that discrimination between ridesharing passengers may discourage further use of such services (Middleton & Zhao, 2019; Moody et al., 2019). Racial bias in the sharing economy has been uncovered in Norway, indicating it is not merely an American phenomenon (Nødtvedt et al., 2021). Ridesharing motivation may also be impacted by environmental concerns (Raza et al., 2023). Recent literature summaries suggest that there is still much to learn about ridesharing in general, and research needs to investigate how these findings relate specifically to SAVs (Si et al., 2023).

There are gender differences in how public transport environments are perceived (Chowdhury & Van Wee, 2020; Polydoropoulou et al., 2021), even in safe egalitarian countries like Norway (Backer-Grøndahl et al., 2007). Perceptions and concerns about SAVs may also differ on the basis of sociodemographic factors (Barbour et al., 2019; Useche et al., 2021). Age, gender, and experience with technology is suggested as moderators in the UTAUT2, and these relationships have been found to be both direct and indirect (Venkatesh et al., 2016; Wang et al., 2022). Other contextual variables have been found to be effective predictors as well, like respondents' income, how tech-savvy they are, and their travel habits (Bazilinskyy et al., 2015; Blut et al., 2022; Nordhoff et al., 2019; Sener et al., 2019). Tech-savviness often include interest in and use of novel technology. These effects have been suggested as both direct and as moderators, but others suggest a negative shift in public perception of AVs with increasing knowledge of the technology (Aasvik, Hagenzieker, Ulleberg, et al., 2024a; Othman, 2023).Young men have traditionally been found to prefer performance expectancy (or its equivalent 'perceived usefulness', Blut et al., 2022). It seems important to consider and explore the effects of sociodemographic variables when measuring acceptance of SAVs. However, more research is needed to assess their role in SAV acceptance and how they interplay with core concepts of the UTAUT.

There is some variability in which factors that are deemed most efficacious in predicting intentions to use SAVs. Factors such as trust and safety, hedonic motivation, social influence, and performance expectancy are often found as important (Aasvik, Hagenzieker, Ulleberg, et al., 2024b; Chien et al., 2016; de Winter & Nordhoff, 2022; Korkmaz et al., 2021; Nordhoff et al., 2020). Some facets are also hypothesized as more fundamental than others, such as trust and safety, and efficiency (Nordhoff et al., 2023). Research also suggest that acceptance of AVs is adequately explained by a single *General Acceptance Factor* (GAF), as the UTAUT elements often share large correlations (Blut et al., 2022; de Winter & Nordhoff, 2022; Nees & Zhang, 2020; Nordhoff et al., 2018). Using cross-country validation and more than 18 000 respondents, researchers used principal component analysis to find the GAF to be the best statistical representation of 41 variables from the UTAUT and MAVA frameworks. Other factor structures explored were highly correlated, suggesting that the single factor accounting for 55 % of the variance was the best fit. This has important implications for the design of future research, and the authors critique the construct proliferation and compares it to the general intelligence factor *G* (de Winter & Nordhoff, 2022; Schmidt, 2017). Issues regarding sibling constructs are not novel in psychology, as jingle-jangle-fallacies and simplifications in theory building may exacerbate the crisis of replication and reputation in the field (de Winter & Nordhoff, 2022; Fried, 2020; Lawson & Robins, 2021; Smaldino, 2017). Thus, there may be an argument to be made that the theoretical boundaries between constructs in the UTAUT are more theoretical than practical in this context. However, other research has found grounds for more than one acceptance factor (Kacperski et al., 2021; Rahimi et al., 2020; Yuen et al., 2020). Further research is crucial to ascertain whether acceptance of AVs should be represented as a single latent variable or multiple latent variables. It is also crucial to understand how these findings can be applied to the acceptance of SAVs within the realm of public transportation.

There is ongoing pilot testing of SAVs as part of the public transport system across Europe and beyond (Hagenzieker et al., 2021). These tests often involve small vehicles (six to eight passengers), operating at slow speeds (max 15 km/h) and SAE level 3 (Hagenzieker et al., 2021; SAE International, 2021). Many of these also operate on short routes outside regular public transport environments (Hagenzieker et al., 2021). Due to these constraints, research investigating acceptance of SAVs leave many potential riders to conjecture about this future transport mode. Several investigations find mostly optimistic attitudes towards AVs in general (Liljamo et al., 2018; Nordhoff et al., 2022; Schoettle & Sivak, 2014), and respondents grow more positive the more they think about it (Tennant et al., 2016). Additionally, bias from researchers familiar with the subject may impact the results of such investigations (Delbosc, 2022). Future research should seek to strike a balance between informing participants about realistic scenarios and gauging their unaffected perceptions. Caution is also needed when extrapolating findings between different cases using different levels of technology. Basing research on sound theoretical foundation is key to navigating the many factors important in SAV acceptance.

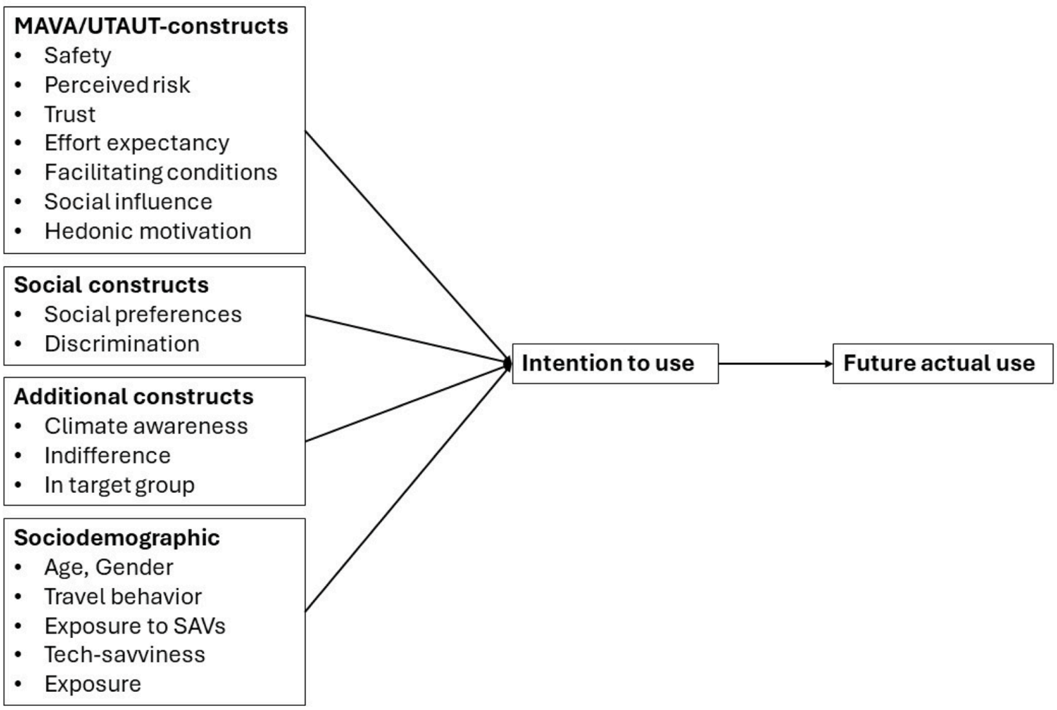

Fig. 1. Conceptual model for the current study.

1.2. Study aims and research questions

Research discussed thus far has explored various factors influencing technology acceptance. Models such as the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Multi-Level Model of Automated Vehicle Acceptance (MAVA) have previously been applied in different contexts. The literature review showed that satisfaction with current transport modes has been incorporated to increase predictive explanatory power of the models to very high levels. It is also evident that social, demographic, and contextual factors influence acceptance, with trust, safety, and efficiency deemed fundamental. Recent studies suggest a General Acceptance Factor (GAF) as the best fit for representing AV acceptance, leaving the theoretical boundaries between constructs in UTAUT open for debate. Variations in the application of both theory and the assessment of specific technologies continue to create challenges for researchers trying to establish consistent methods for measuring SAV acceptance.

Challenges remain in contextualizing research on AVs, especially shared AVs in public transport settings. Furthermore, the previous frameworks have often been extensive and without standardized measurements, making them difficult to use in practical settings. The current paper seeks to fill this research gap. We suggest new extensions to enhance prediction of SAVs as opposed to privately owned AVs and to find the most efficient categorization of these predictors. Fig. 1 shows the chosen conceptual model for the current study derived from previous research.

Thus, the current study intends to provide a step towards a more accurate measure of people's acceptance of SAVs employed in public transport. This will be achieved using three research questions.

1) We will explore the structure of items that measure the factors suggested primarily by the MAVA and items thought to be important in the novel social setting of SAVs. They will be subjected to principal component analysis.
2) We aim to run confirmatory factor analysis of the suggested factor structure to improve reliability of results.
3) We will examine how well these factors perform in a multiple regression analysis predicting intention to use SAVs.

We seek the development of a concise and practical battery of items that measure intention to use SAVs. This battery could prove important in the coming years as the technology grows more mature and widespread. Public transport providers and researchers could deploy this battery to succinctly and efficiently gauge how people respond to novel developments in SAV technology.

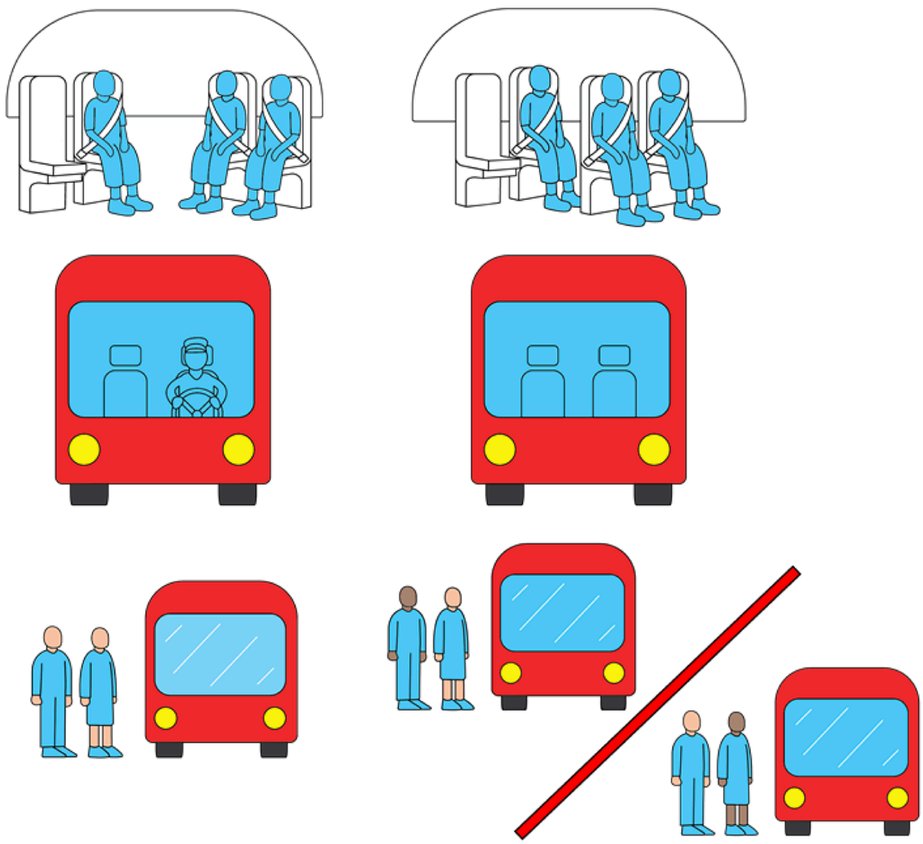

Fig. 2. Informational illustrations given to participants about a possible future SAV service. This was accompanied by some text. Participants only saw one of the three pairs of illustrations.

2. Materials and methods

2.1. Sample size and recruitment

We wanted to explore these research questions by administering an online survey. Participants were recruited through two main channels, but the SMS recruitment had a very poor response rate of 3 %. Because of this, we resorted to inviting participants of a previous survey who had agreed to be contacted with future surveys. This email list consisted of 8892 unique addresses. They had responded to an online survey conducted by the same research team as the current papers' authors about infrastructure and maintenance for cyclists and pedestrians (parts of those results are published here: Aasvik & Bjørnskau, 2021). After inviting these, we ended up with 2141 respondents (approximately 20 % response rate). All responses were gathered during the summer of 2022.

2.2. Measurements

All items in the survey were measured on a Likert-scale ranging from 1 "Totally disagree" to 5 "Totally agree" with a sixth option "Not relevant/do not know" unless otherwise specified. When calculating means of scales, we recoded "Not relevant/do not know" into the mid-point of the scale (3). To minimize participants' need for conjecture about the largely unknown future SAV service, we included explanatory text and illustrations:

> *You will now receive information about a future bus service that may be common in Norway in a few years. The vehicles will look like small buses and be self-driving. You order and pay for the service through a smart-phone app. The bus will come and pick you up where you are or at a bus stop, and you may have to share it with others traveling in the same direction. This self-driving bus will only be available through order and will not necessarily follow usual bus stops.*

Thereafter followed illustrations as shown in Fig. 2.

These were shown along with a short text explaining the illustrations' content. The alternative versions of the three pairs of illustrations were randomly shown to equal sub-groups of the sample and were thought to give a wide impression about what such a service may look like. The information and illustrations were approved by the main public transport authority in the Oslo-region, Ruter.

In the study, we first gathered informed consent and socio-demographic information, before displaying the information about SAVs. After the information, we presented MAVA-items and its' extensions. More sensitive topics, such as discrimination and income, were placed last in the survey. The data collection was vetted by Norwegian Agency for Shared Services in Education and Research (Sikt) and found to be in accordance with ethical and legal guidelines.

2.2.1. Socio-demographic information and contextual variables

We included six socio-demographic and micro-level variables: age (measured on eight ten-year intervals from under 19 years to over 80 years), gender, public transport use (binary), household income (measured on three levels), tech-savviness, exposure to SAVs.

The age groups were distributed: 0.1 % under 19, 5 % 20–29, 12 % 30–39, 18 % 40–49, 24 % 50–59, 24 % 60–69, 15 % 70–79, and 2 % over 80. The sample consisted of 36.5 % females, and 48.7 % used public transport regularly. Roughly half (48.3 %) reported a

Table 1
MAVA-items included in the current study and their corresponding MAVA-factor.

MAVA-factor	ID	
Effort expectancy/Facilitating conditions	*M1*	I believe it would be easy for me to use this bus service
Safety/Perceived risk/Trust	M2	I would feel safe while waiting for such a bus when it's dark
	M3	I would be afraid of uncomfortable social situations on board such a bus
	M4	I would be afraid that someone could hack the bus's data system
	M5	This bus would be risky to use
	M6	Such a bus would increase traffic safety
	M7	I would trust such a bus
Service and vehicle characteristics/perceived benefits/performance expectancy	M8	I think this type of bus will be useful for me
	M9	It is important that the bus has a nice design
	M10	It is important to me that the bus is comfortable
	M11	It is important that the bus does not extend my travel time
	M12	Such a bus would be better than a traditional bus
Social influence/Norm	M13	I think others would think it's good that I use such a bus
	M14	I think most people would want to use such a bus
Hedonic motivation	M15	Using such a bus would be entertaining
Behavioral intention	M16	I would use such a bus when they become available
	M17	I would try this bus service if it became available where I live
	M18	I would not use the bus service even if it became available

gross household income of 750 000—1 500 000 NOK, with equal distribution on both ends.

Tech-savviness was an aggregate of 1) whether they were among the first to adopt new technology, 2) whether they knew about the trials with SAVs in the Oslo area, 3) whether they used adaptive cruise control if available, and 4) whether they used advanced driver assistance systems when available. Most people (71.8 %) regarded themselves as average in using new technology. Only 8.8 % of the sample knew nothing about the pilots using SAVs in the Oslo region.

Exposure is an aggregate score of whether they had seen a SAV and whether they had tried one. Two out of three (66.1 %) had never seen the buses and 6.3 % had tried the vehicles at least once.

2.2.2. MAVA

One of the main goals of the current study is to create a concise measure of MAVA-constructs. To this end, we examined numerous previous investigations of both MAVA and UTAUT (Acheampong & Cugurullo, 2019; Backer-Grøndahl et al., 2007; Bansal et al., 2016; Choi & Ji, 2015; Delle Site et al., 2011; Hohenberger et al., 2016; Korkmaz et al., 2021; Krueger et al., 2016; Madigan et al., 2017; Nordhoff et al., 2019; Raue et al., 2019; Sener et al., 2019; Venkatesh et al., 2012; Xu et al., 2018; Zhang et al., 2020). From these papers, we selected items that were the most relevant for our purposes. We also made sure that these items did not have too much overlap in semantic content between each other. This process resulted in 18 items to cover the MAVA-constructs. The items were translated to Norwegian by the bilingual authors of the current paper. The items were chosen to capture key aspects of the model, such as trust, risk assessment and service characteristics. Brevity of the survey was a limiting factor. Table 1 presents these items and their corresponding MAVA-constructs. A more expansive version can be found in the appendix.

MAVA-items were intentionally constructed to keep the scale as short as possible, while covering all aspects of the framework. This resulted in some factors being measured by several items. We also grouped MAVA-factors that have been suggested as theoretically similar and empirically correlated, like perceived benefits and performance expectancy. Items were also adapted to the Norwegian context in 2022, where most people are unaware of the future capabilities of such a service.

2.2.3. Social preferences & discrimination

For the extension of MAVA to capture social elements, we hypothesized two separate factors: social preference and discrimination. These were each captured using three items. Social preference was inspired by previous research about ridesharing, as well as interpersonal distance and sharing anxiety (Bansal et al., 2016; Cunningham et al., 2019; Dolins, 2021; Haboucha et al., 2017; Hall, 1966; Sovacool & Axsen, 2018). For items measuring discrimination, we used research about ridesharing discrimination focusing on age, gender, and ethnicity (Backer-Grøndahl et al., 2007; Ceccato, 2017; Chowdhury & Van Wee, 2020; Cunningham et al., 2019; Middleton & Zhao, 2019; Moody et al., 2019). These items are shown in Table 2.

The two sets of items were thought to give a detailed description of how respondents assess the social situation aboard small, unmanned vehicles.

2.2.4. Engagement, target group, and climate

We also included a second group of extension-items to the MAVA-factors. These were enthusiasm for the service, perceiving to be in the target group, and beliefs that it is important to change transport infrastructure to match climate targets. Climate is an oft-cited benefit of electric SAVs, and could be an important motivator for using the service (Haboucha et al., 2017; Jones & Leibowicz, 2019; Kyriakidis et al., 2015; Liu et al., 2019; Nazari et al., 2018; Wu et al., 2019; Yap et al., 2016). Transport behavior is largely habit-driven, and being enthusiastic about SAVs' impact in one's everyday life could also be an important predictor of intentions to use (Blut et al., 2022; Venkatesh et al., 2012). These items are presented in Table 3.

The items are not necessarily related but are considered important factors that differentiate AVs implemented as privately owned cars and AVs implemented in public transport.

2.3. Analysis

The analyses were performed using the Jamovi software version 2.4.11.0 and Mplus version 8.10 (Muthén & Muthén, 2017; The Jamovi Project, 2021). Considering our large sample size, we will be wary of striking a balance between type 1 and type 2 errors. When looking at effect sizes, in addition to p-values, we circumvent some problems associated with overreliance on p-values alone (Amrhein et al., 2019; Wasserstein & Lazar, 2016; Ziliak & McCloskey, 2008). Cronbach's alpha levels are interpreted using Nunnally's guide

Table 2
Social preference and discrimination items with translations.

Social preference &Discrimination items	ID	English
Dislike proximity	S1	I dislike being seated so close to others
Enjoy other passengers (R)	S2	I would enjoy riding in such a bus with others
Will not talk to strangers	S3	I do not wish to talk to strangers in such a bus
Not use with youths	D1	I do not want to use this bus if it is mostly used by youths
Women shouldn't use	D2	Women should avoid sharing these buses with unfamiliar men
Ethnicity unsafe	D3	Sharing this bus with foreigners or people of different ethnic origin would make me unsafe

Table 3
Extraneous items covering climate, indifference, and perceiving oneself in the target group for SAVs, N = 1902.

Items	ID	English
Climate targets transport	E1	It is important to take measures to mitigate climate emissions from transport
Indifference towards bus	E2	I am indifferent towards this self-driving service
In target group [a]	E3	Do you believe you are in the target group for such buses?

Note. [a] This question used a "1 − To a very small degree" to "5 – to a very large degree" Likert scale.

from 1994, keeping its' limitations in mind (Lance et al., 2006; Nunnally, 1994). We opted for a principal component analysis (PCA) to explain the most variance in our data using the fewest possible variables. Previous research has uncovered large correlations between the UTAUT-constructs (Blut et al., 2022), and MAVA-constructs have been found to represent one factor (de Winter & Nordhoff, 2022). The PCA is suitable because it assumes that variance in the items cause the variance in the principal component, not that the latent variable cause variance in the indicators. This approach is in line with the current hypothesis.

The current study shares data with another publication (Aasvik, Ulleberg, et al., 2024). They share the same participants, socio-demographic information, MAVA-items, and suggested extensions. However, while the current publication focuses on investigating the component structure of acceptance, the other publication involves an experimental manipulation and six sets of personality constructs. These constructs are used to predict different MAVA-factors. These study aims are different and involve using partly different sets of variables. They do inform each other and will be cross-referenced but are developed as separate manuscripts. The anonymized raw data set is posted on the Open Science Framework (Aasvik, 2022).

Sample sizes required for proper power in principal components analysis is largely contingent upon study design (Bandalos & Boehm-Kaufman, 2010). Common criteria often suggest having a large subject to item-ratio (Osborne & Costello, 2019). Others find that some of these rules of thumb perform poorly in practice (Rouquette & Falissard, 2011). Our intentions were to test a set of 15 items pertaining to the MAVA framework excluding intention to use. In addition, we wanted to test nine extraneous variables relevant to the social situation inside SAVs. A total of 24 items would be subject to principal components analysis, suggesting a total sample of 1200 participants using a $N = 50$ sample per item norm. This may be an exaggeration, especially given that most rules of thumb would require less participants per item when $N > 200$ (DeVellis, 2012).

Our gross sample consisted of 2141 participants. Two of these were incomplete and one stated that their response should be removed due to dishonesty. An attention check was used, asking participants whether the seats they were shown were in the driving direction or facing the other passengers. 236 participants (11 %) failed to pass. This left 1902 participants who were brought forward to analysis. This exceeds our previous estimate of 1200 participants, meaning that our study may be well-powered for its' intended purposes.

To test the component structure of the MAVA and UTAUT for SAVs, as well as novel items pertaining to the social situations arising inside, we performed a split-sample analysis. This common strategy ensures that the factor structure identified by exploratory analyses (PCA) is not an artifact of overfitting to a single dataset. Conducting CFA on a separate sample validates that the factor structure is robust and generalizable (Lorenzo-Seva, 2021).

The sample was therefore randomly divided into two equal halves. The first sub-sample (N = 950) was subjected to principal component analysis (PCA), and the second sub-sample (N = 951) to confirmatory factor analysis (CFA). The sample sizes were deemed sufficient, as they exceeded the rule of thumb of N > 200 cases. Moreover, the KMO values were almost identical in the two samples (0.930 and 0.931), resulting in a communality ratio of 0.999. Thus, the two sub-samples can be regarded as equivalent in the context of factor analysis (Lorenzo-Seva, 2021).

Three indicators were used in CFA to compare the fit of different factor structures generated from the PCA.: the Comparative Fit Index (CFI), the Tucker-Lewis Index (TLI), and the Root Mean Square Error of Approximation (RMSEA). Higher values of CFI and TLI, preferably above 0.90, along with lower values of RMSEA, preferably below 0.08, indicate a better model fit (Hu & Bentler, 1999). These recommended cut-off values are, however, based on analysis of continuous data. However, the Likert-format data in the present study can be regarded as ordered categorical data, and this measurement level should be considered when model fit measures are estimated (see, e.g. Xia & Yang, 2019). The conventional cut-off values for model fit are also not established for this level of measurement, and the use of RMSEA, CFI, and TLI are therefore more appropriate as tools for model comparison and improvement rather than absolute cut-off values (Xia & Yang, 2019).

To make the measures of model fit reliable, the variables were treated as ordered categorical data, and the Weighted Least Squares (WLSMV) estimator was used to estimate the confirmatory factor analyses in Mplus (Muthén & Muthén, 2017).

3. Results

3.1. Principal component analysis

We performed a principal component analysis (PCA) of the 15 items measuring MAVA constructs and the nine suggested extensions, totaling 24 items. For the main test of the 24 items, Bartlett's Test of Sphericity was significant ($\chi 2$ (df = 276) = 9552, $p < 0.001$) and the KMO measure of sampling adequacy was 0.931, suggesting good suitability. The Scree Plot and simulated parallel analysis Eigenvalues are shown in the appendix.

A four-component solution is supported by using parallel analysis. A fifth component also has an Eigenvalue marginally over one, but this solution was deemed sub-optimal. The Scree Plot would support both two and four components. Thus, we choose four components as suggested by parallel analysis.

The four-component solutions' component loadings are presented in Table 4. Component loading under 0.3 are suppressed as per convention (Field, 2013).

Most items have similar variance and mean. Most answers are towards the higher end of the scale, above three. Not increasing travel time scored highest and thinking that the service would be better than a traditional bus scored lowest among MAVA-items. Most respondents think it is important to limit emissions within transport. The lowest score is whether people of different ethnic backgrounds make respondents feel unsafe onboard a SAV.

The suggested four component structure includes 1) MAVA-items and suggested extensions, 2) four items about interpersonal security or discrimination, 3) three items about social preference or sociability, and 4) three items regarding attractivity, design and travel time. The question about climate does not have a large loading on any one factor and does not semantically fit into any of them and is therefore not carried forward for further analysis. The extraneous questions about "indifference towards bus" and "in target group" had a higher factor loading and were thus included in the first factor.

Three items originally put as MAVA-items are grouped in its' own fourth component. The two suggested social extension categories are also kept separate, suggesting that these cover separate variance. Trust seems to be the most central single item across the suggested structure, yielding the lowest score on uniqueness, closely followed by usefulness.

The four extracted components show varying internal consistency. "Interpersonal security" and "Sociability" score low, but acceptable for such short scales. "Attractivity" does not seem to meet psychometric standards. Similar values were found in the other half of the sample, with $\alpha = 0.92$ for the MAVA, $\alpha = 0.73$ for Sociability, $\alpha = 0.71$ for Interpersonal security, and $\alpha = 0.39$ for Attractivity. The components mostly show weak correlations, suggesting that they each measure different aspects of perception of SAVs. The correlation between PCA MAVA and Sociability is medium by some standards (Cohen, 2009), suggesting that this may be a considerable aspect of SAV perception.

3.2. Confirmatory factor analyses

Based on the results from the Principal Component Analysis, we compared the fit of three different models to the data. These models

Table 4
Means, standard deviations (SD), and suggested component structure of the principal component analysis, N = 950.

	ID	Mean (N = 1902)	SD (N = 1902)	1:MAVA	2: Interpersonalsecurity	3:Sociability	4: Attractivity	Uniqueness
Cumulative % of variance				*29.2*	*38.8*	*48.2*	*54.3*	
Eigenvalue				*7.83*	*2.59*	*1.32*	*1.29*	
Trust the bus	*M7*	3.31	1.09	0.87				0.24
Useful to me	*M8*	3.26	1.11	0.84				0.28
Better than regular bus	*M12*	2.91	1.09	0.81				0.38
Improve traffic safety	*M6*	2.96	1.04	0.81				0.35
Easy to use	*M1*	3.55	1.05	0.78				0.39
Risky use (R)	*M5*	3.34	1.04	0.76				0.34
Descriptive norm	*M13*	3.11	0.95	0.69				0.50
In target group	*E3*	2.92	1.23	0.67				0.46
Injunctive norm	*M14*	3.31	0.88	0.65				0.55
Safe wait while dark	*M2*	3.27	1.07	0.65				0.53
Indifference towards bus	*E2*	2.57	1.13	−0.57				0.59
Would be entertaining	*M15*	3.17	1.08	0.57				0.55
Afraid of hacking (R)	*M4*	3.18	1.10	0.43			−0.34	0.60
Women shouldn't use	*D2*	1.89	0.94		0.82			0.35
Ethnicity unsafe	*D3*	1.75	0.86		0.77			0.38
Not use with youths	*D1*	2.38	1.01		0.66			0.47
Climate targets transport [a]	*E1*	4.17	1.05	0.31	−0.37			0.69
Will not talk to strangers	*S3*	2.99	1.07			0.85		0.34
Dislike proximity	*S1*	2.84	1.01			0.77		0.31
Enjoy other passengers (R)	*S2*	2.72	0.86			0.68		0.41
Afraid of social on-board	*M3*	2.65	1.10			0.36		0.52
Comfort important	*M10*	3.92	0.69				0.70	0.52
Nice design important	*M9*	2.95	1.00				0.55	0.61
Don't increase travel time	*M11*	4.23	0.75				0.54	0.62
Inter-component correlations and internal consistency								
MAVA		3.21	0.76	*α = 0.92*				
Interpersonal security		3.70	0.55	0.209	*α = 0.72*			
Sociability		2.80	0.76	0.318	−0.259	*α = 0.75*		
Attractivity		3.70	0.55	−0.098	−0.112	−0.069	*α = 0.36*	

Note. Oblimin rotation was used due to the expected correlation between components. Component values under 0.30 are suppressed. [a] = item not included in any resulting components due to low loadings and theoretical fit.

were 1) one single general factor, 2) four factors with MAVA and the three categories of extension, or 3) two factors with a MAVA factor and a seven-item social dimension factor (the six items suggested as extensions and “afraid of social on-board” as suggested by PCA). Table 5 presents the model fit indices for these three models using 23 items.

The results from the confirmatory factor analyses (Table 5) indicated that the one-factor model did not fit the data well. In contrast, the four-factor solution demonstrated a significantly improved fit compared to the one-factor model. Although the model incorporating one general factor and one social factor showed better fit than the single-factor model, it still exhibited sub-optimal fit.

The four-factor solution clearly provided the best fit to the data. Further modifications to this factor model were not implemented, as the primary objective was to compare the fit of different factor structures to the data.

3.3. Correlations

We ran correlation analysis to investigate bivariate relationships between the main study variables on all study participants (N = 1902). For this analysis factor 4 “Attractivity” was excluded due to the low internal consistency of the scale. This correlation matrix is presented in the appendix.

Intention correlates moderately with several factors, including tech-savviness, PCA Interpersonal security, and PCA Sociability. It shares a large linear relation with PCA MAVA. Other socio-demographic variables correlate weakly or not at all with intention to use.

Gender mostly does not share linear relationships with PCA constructs, while age and income does. Tech-savviness also seems central to MAVA.

3.4. Regression models

We wanted to test our components in predicting intention to use SAVs. We ran three OLS multiple regression models to see the impact of each segment of predictors. These analyses were performed on the total sample (N = 1902). For interaction effects, the relevant terms were z-transformed to minimize problems with multicollinearity. For these regression models, factor 4 “Attractivity” was excluded due to the low internal consistency of the scale. These results are presented in Table 6.

The first model has a low explained variance at nine percent. The largest effect sizes are using public transport and being tech-savvy. Gender barely reaches the traditional $p < 0.05$ threshold.

The second model has a significant increase in explained variance. The MAVA-construct has a large standardized regression coefficient and diminishes the effect of other variables. The other two PCA constructs reach $p < 0.05$ with smaller effect sizes. Public transport use remains significant.

In a third model, we tested whether the three PCA constructs interacted with age and gender, testing moderation effects. For this analysis, we z-transformed the interaction terms to avoid issues with multicollinearity. We found no significant interaction terms with age, but two with gender: MAVA and sociability. These suggests that the effects of these two differ over the levels of the gender variable, such that women show a stronger relationship between these two and intention to use SAVs. This model did not add any explained variance.

We explored introducing “useful to me” and “trust the bus”, which were the most central MAVA-items in the PCA. This was done in a separate model, in a separate second step after socio-demographic variables. This model yielded an adjusted R^2 of 0.712. The subsequent jump in explained variance when including the three other PCA constructs was $\Delta R^2 = 0.055$, $p < 0.001$. While still a statistically significant increase of 5.5 %, it highlights how the MAVA-items interrelate closely and that there may be room for simplification.

4. Discussion

The current paper investigated the structure of variables that predict intentions to use SAVs in public transport. We created items based on previous research on UTAUT and MAVA frameworks and tested novel items that account for the social situation within small ridesharing vehicles. We explored different component solutions using PCA and CFA. A four-component solution suggesting that MAVA, interpersonal security, sociability, and attractivity features are best conceptualized separately, was chosen. Our results suggest that there is room for simplification in measuring intentions to use SAVs. Most of the explained variance in intention to use SAVs can be accounted for using only two items, with the added variance from including 22 additional items being negligible. Principal component analysis and linear regression indicate that usefulness and trust of the SAVs are the most central and most efficacious predictors of intentions to use SAVs. Sociability and interpersonal security are also significant predictors, albeit less so than the aggregated MAVA construct.

Table 5
Three confirmatory factor analyses and their fit indices from CFA with WLSMV-estimation with 23 items, N = 951.

Models (number of factors)	*df*	X^2	$\Delta\chi 2$[a]		CFI	TLI	RMSEA
One general factor (1)	230	4600	–		0.821	0.803	0.141
Four factor solution from PCA (4)	224	1572	1111	***	0.945	0.937	0.080
One general factor and one social factor (2)	229	2345	722	***	0.913	0.904	0.099

[a] Difference from the one-factor model. *** = $p < 0.001$.

Table 6
Regression coefficients from the components suggested by PCA and contextual variables predicting the intentions to use SAVs, N = 1902.

	Model 1					Model 2					Model 3				
	Beta	**95 % CI**		***p***		***Beta***	**95 % CI**		***p***		***Beta***	**95 % CI**		***p***	
Age	−0.04	−0.09	−0.03	0.048	*	0.01	−0.02	0.03	0.570		0.01	−0.02	0.03	0.534	
Men (0) – Women (1)	0.04	−0.01	0.09	0.103		−0.01	−0.03	0.02	0.556		0.00	−0.03	0.02	0.795	
Income	0.04	0.00	0.09	0.070		−0.01	−0.03	0.01	0.433		−0.01	−0.03	0.01	0.469	
Public transport use	0.15	0.11	0.19	<.001	***	0.05	0.02	0.07	<.001	***	0.05	0.02	0.07	<.001	***
Exposure	0.01	−0.03	0.05	0.650		−0.01	−0.04	0.01	0.223		−0.02	−0.04	0.01	0.167	
Tech-savviness	0.25	0.21	0.30	<.001	***	−0.02	−0.04	0.01	0.183		−0.01	−0.04	0.01	0.377	
PCA MAVA						0.85	0.82	0.88	<.001	***	0.85	0.82	0.88	<.001	***
PCA Sociability						−0.03	−0.06	0.00	0.023	*	−0.03	−0.06	0.00	0.021	*
PCA Interpersonal security						0.03	0.00	0.05	0.030	*	0.03	0.00	0.05	0.033	*
Age PCA MAVA [a]											0.00	−0.03	0.03	0.893	
Gender PCA MAVA mean [a]											0.06	0.03	0.09	<.001	***
Age PCA Sociability [a]											0.01	−0.02	0.04	0.440	
Gender PCA Sociability [a]											0.03	0.01	0.06	0.013	*
Age PCA Interpersonal security [a]											0.01	−0.01	0.03	0.417	
Gender PCA Interpersonal security [a]											0.01	−0.01	0.04	0.249	
Adjusted R^2		*0.09*				*0.75*					*0.75*				

Note. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. [a] = interaction terms were z-transformed to avoid issues with multicollinearity.

4.1. Factor solutions

From the literature review, it seems that employing different theoretical approaches beget different results when predicting acceptability of SAVs or AVs in general (Jing et al., 2020). While researchers often use UTAUT or its' constituent theories in investigating AV acceptance, there is an abundance of research adding their own concepts or testing novel items (Bellet & Banet, 2023; Jing et al., 2020; Nordhoff et al., 2019; Venkatesh et al., 2016). There is also a lack of standardization in question formulation when enquiring about UTAUT-factors in AVA. Furthermore, the concept in question, namely AVs, are under quick development and can look very different from study to study (Hagenzieker et al., 2021; Narayanan et al., 2020). One should be careful to extrapolate between these different cases. Thus, there is a proliferation of research investigating similar, but not identical technologies, and using similar, but not identical, theoretical grounding. Much of the difference in factor structure and explanatory power for predicting acceptance of AVs and SAVs, may thus be explained by differences in theory or in the technology in question.

The four-component structure of our current study may be a result of our theoretical approach. We sought to use MAVA-variables and investigate whether and how these would interact with variables concerning the particulars of SAVs. While the bulk of MAVA-items cluster together, we find that some items are not best conceptualized by a single component. Additionally, it seems that the social aspects are also best conceptualized as extraneous to the MAVA/UTAUT-model. While others have extracted a single component explaining 55 % of the variance, our first component only accounted for 29 % (de Winter & Nordhoff, 2022). Similar research suggesting a general acceptance factor (GAF) find some multidimensionality to the acceptance of AVs (Nees & Zhang, 2020). Other research has also found four components to SAV acceptance, although not quite the same ones as the current study (Kacperski et al., 2021). They found safety, sustainability, efficiency, and privacy. Although that investigations' questionnaire was not founded in UTAUT factors, it builds a case of complexity in predicting user acceptance of SAVs. It may seem that the core of the GAF encompasses some of the most important predictors of intention to use AVs. Other factor solutions may also be viable depending on context or research objectives. This is also supported by our regression results, where the single GAF had the largest effect size, but the other two factors also proved significant. The GAF also shows a large correlation with the intention to use construct, hinting at a limited difference between the two constructs. While some have found even higher levels of explanatory power, the high level of explained variance in our model suggests that there is limited room for additional variables to explain even more (Bellet & Banet, 2023). While some variance surely is due to the error term and random variance in the responses, there still seems to be some room for improvement here, for example by introducing satisfaction with current mode of transport.

The results suggests that there may be a latent GAF influencing the acceptance of both AVs and SAVs. Multivariate analyses suggest that, while other factors share significant linear relations with intention to use, most of these effects are diminished when controlling for the PCA MAVA factor, which is our approximation of a GAF. This lends further credence to the notion that research investigating UTAUT factors, and the numerous extensions thereof, may be of little added value (de Winter & Nordhoff, 2022). While some of the suggested extensions in the current study were included in our GAF, these did not ultimately further the explanatory power of the GAF on intention to use. This view is corroborated by the large correlation shared between these constructs in the current study and similar research (Blut et al., 2022; de Winter & Nordhoff, 2022; Korkmaz et al., 2021). In fact, only two items seem to be sufficient to capture the essence of the GAF in our sample, explaining upwards of 70 % of the variance in intention to use SAVs. This has large implications for the future of research on acceptance and intention to use AVs and SAVs.

Social factors seem to be of some value for explaining intentions to use SAVs. Placed on different components, sociability and interpersonal security do not significantly add to the explanatory power of the MAVA. The two constructs share substantial correlations with intention to use and show significant small effects on intention to use in the multiple regression. This may echo sentiments from previous research that the social situation is thought of as the normal situation while using public transport (Aasvik, Hagenzieker, & Ullegerg, 2024). It seems that the presence of other passengers may only be a problem if they impact the two most central facets of the MAVA: trust and usefulness. Previous research has suggested that potentially increased travel time, and thus lower usefulness, is more important than the presence of a stranger (Krueger et al., 2016; Lavieri & Bhat, 2019). Similarly, ridesharing seems mostly problematic if it infringes on the respondents' safety and trust (Barbour et al., 2019; Krueger et al., 2016; Sanguinetti et al., 2019). While passengers may be willing to pay more to not share an AV, this does not seem to affect their overall willingness to use SAVs (Clayton et al., 2020). Social factors are therefore of limited and subordinated importance, but may still play a role in people's perception of the service.

The answer to our research questions is thus that a single GAF may be the simplest solution, most reliable, and most efficacious predictor of intentions to use SAVs. While a four-factor solution is favored to account for all items included in this survey, a single GAF by far shows the largest effect size in predicting intentions to use SAVs. This factor is measurable only by a few items. For applications where brevity and efficiency are favored, this does seem to be a reasonable approach. But this may not always be the best option for future research. Research suggests that different aspects of SAV acceptance are impacted by different individual-level predictors (Aasvik, Ulleberg, et al., 2024). For research investigating more fine-grained aspects of social situations, a more nuanced approach may be in order. Our four-component solution further suggests that sociability and interpersonal security are distinct categories. Additionally, the fourth component of attractivity should be further examined, as it showed too poor internal consistency to be used in inferential statistics in this paper. While some suggest that UTAUT-items are equally able to explain intention to use autonomous cars, robo-taxis, and autonomous air mobility vehicles, our results suggest that there may be other factors that influence perception of SAVs (Bellet & Banet, 2023). Further research is needed to determine the contexts in which these additional components are most useful.

4.2. Prediction

We ran three models predicting intention to use SAVs. The first model consisted of background variables suggested by previous research (Nordhoff et al., 2019; Venkatesh et al., 2016; Wang et al., 2022). While sociodemographic effects are much cited, they often disappear when controlling for psychosocial factors (Nordhoff et al., 2019). We see that effects of age, gender, income, travel habits, tech-savviness, and exposure are smaller in the second step of the regression model. Using public transport remain significant, albeit with smaller beta coefficients. Age and gender are often conceptualized as moderators of effects, like performance expectancy being more important for young men (Blut et al., 2022; Venkatesh et al., 2016). We tested some interactions between our PCA components, and age and gender. There were no interactions with age and just two with gender, suggesting that the effects of MAVA and sociability are stronger for women. This implies that sociodemographic variables are less important when other factors are properly controlled for, but hints that they may play a role in different contexts. We did, however, not capture every suggested moderated effect, and further research could further investigate this.

The second-step regression models added the PCA constructs. This served as the largest jump in explained variance we were able to achieve. The efficacy of MAVA as a predictor, and its' large correlation with intention to use, may indicate that the two constructs are too similar. Perhaps intention should be included as a part of the GAF, as is indicated in our additional PCA. While the notion of intention as a determinant of people's behavior has a long tradition in theories such as the theory of reasoned action (TRA), it is not always the best conceptualization (Fishbein & Ajzen, 1975). It may seem that intentions to use SAVs are just as well thought of as a sub-construct in a general acceptance factor. A real test of this hypothesis would of course only be possible when actual behavior, namely use of SAVs, is more prevalent in a given population.

A potential explanation for the substantial shared variance among the various items measuring MAVA could be the presence of Common Method Variance (CMV). CMV is characterized by shared variance that is more attributable to the measurement method than to actual similarities in the constructs being measured (Podsakoff et al., 2012). In this study, the use of uniform phrasing and scale formats might have contributed to an increase in CMV. However, if CMV were a significant concern in this study, one would also expect a similarly high correlation between the items measuring interpersonal security, sociability, and attractiveness, and a high correlation between these three factors and intention to use SAV. Given that this was not observed, CMV was not considered a significant confounding factor in this research.

We also explored models using just the two most central MAVA-items, namely usefulness and trust. Comparing this models' ability to predict level of intention to use to our other regressions, suggests that the two most central MAVA-items were as efficacious as adding a set of 22 more variables. These two items also coincide with emerging research suggesting that trust and efficiency are the building blocks for AV acceptance (Nordhoff et al., 2023). These items' centrality is corroborated in the current study and suggest great room for simplification when brevity is of the essence. At the same time, such a simplification may be at the cost of understanding the nuances of the GAF. Our interaction terms hint at the possibility that differences between groups of the population may have different opinions about the social situation arising in SAVs. This is corroborated in a recent study and shows the usefulness of including several aspects of SAV perception when investigating in-depth nuances of such a service. Future research should keep investigating the benefits and costs of simplifying or expanding the models in different ways.

Most research using UTAUT-frameworks approach approximately 70 % explained variance in regression models (Venkatesh et al., 2016), and improving this further has long been found difficult (Taylor & Todd, 1995). Therefore, it is not as surprising that the added MAVA-extensions in the current study also follow this trend. That does not necessarily mean that these are unusable in future research. Particularly when comparing different technological solutions or social situations or in longitudinal studies. The fact that all PCA components had significant correlations with intention to use gives credence to the notion that these may still play a role in some circumstances. In fact, research has found that different individual-level predictors mediate different aspects of the MAVA and suggested extensions (Aasvik, Ulleberg, et al., 2024). For example, trait neuroticism plays a larger role for perceptions of safety than for i.e. hedonic motivation. Other individual difference variables, like *Social Dominance Orientation*, seem to govern ratings of importance of social preferences.

4.3. Limitations

While the data used in this study was largely recruited from the Norwegian population, it has its limitations. The sample is not as representative as intended due to technical issues and response rates. We used a sample of previous respondents to other surveys. Those who respond to surveys and agree to participate again, differ from the population in important ways (Groves & Peytcheva, 2008). For example, ours was an elderly sample. This could have skewed the results to align with the preferences of that demographic. The way that the results converged with other studies weakens this suspicion. The effect of age in our regression models also shrinks as other constructs are controlled for, further diminishing the importance of age in this context.

Participants were previously recruited for surveys on different topics such as bicycle infrastructure, and do not necessarily differ from any other sample of survey-responders. This issue is somewhat alleviated by our focus on theory building and component analysis rather than representative perceptions of SAVs. The current study is more concerned with developing new measurement models than with external validity and generalizability of results. Furthermore, there is little reason to doubt that the interaction between constructs suggested in the current paper are generalizable to populations beyond Norway.

The UTAUT and MAVA models suggests that there exist several moderator effects between key components and other individual-level variables. These effects were barely tested in the current study and may provide further insights into key issues, such as the benefits of including multiple aspects of SAV perception.

We provided some information about the largely future SAV transport system. There is a fine line between informing respondents about the topic of the survey and impacting their perceptions. It is probably important to brief participants on the technology in question in studies like these, as the rapidly evolving technology may leave respondents to conjecture about the actual or intended nature of them. This uncertainty on the side of respondents may increase error terms and weaken validity. Future research should keep this in mind while waiting for the service to become more readily available.

4.4. Conclusions

The current study provides several key insights into SAVs acceptance. First, it supports conceptualizing SAV perception as a general acceptance factor (GAF). Furthermore, this GAF seems to be adequately measured by as few as two variables: usefulness and trust. This finding could be important for both researchers and transport agencies, as it suggest a narrow focus on just two key factors in early implementation. This could also simplify acceptance measurement in practical environments. Second, aspects of the social situation and design of the vehicles are best conceptualized as separate components. The two social factors show significant but small effects on intention to use SAVs, suggesting they may play a role. In contexts where nuanced measurement is important and the social situation is highlighted, sociability and interpersonal security could become even more important predictors of intentions to use SAVs. Finally, we caution that the variety of theoretical approaches and different levels of technology may impact the results of such investigations. This trend can create an arbitrary multitude of factors and preclude the realization of simpler models of measurement. More research is needed to validate our suggestion of simplification and to test our findings in a real-world setting.

CRediT authorship contribution statement

Ole Aasvik: Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Pål Ulleberg:** Writing – review & editing, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Conceptualization. **Marjan Hagenzieker:** Writing – review & editing, Supervision, Investigation, Conceptualization.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

A.1. MAVA-items expanded table

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Table 11
MAVA-factor, wording, translations, and most important sources for MAVA-items, N = 1902.

MAVA-factor	Norwegian	English	Most relevant sources
Easy to use Effort expectancy/ Facilitating conditions	Jeg tror det ville vært enkelt for meg å bruke denne busstjenesten	I believe it would be easy for me to use this bus service	(Acheampong & Cugurullo, 2019; Korkmaz et al., 2021; Sener et al., 2019; Venkatesh et al., 2012)
Safe wait while dark Safety/ Perceived risk/ Trust	Jeg ville følt meg trygg mens jeg ventet på en slik buss når det er mørkt	I would feel safe while waiting for such a bus when it's dark	(Acheampong & Cugurullo, 2019; Backer-Grøndahl et al., 2007; Bansal et al., 2016; Korkmaz et al., 2021; Nordhoff et al., 2019; Sener et al., 2019)
Afraid of social on-board (R) Safety/ Perceived risk/ Trust	Jeg ville vært redd for ubehagelige sosiale situasjoner ombord en slik buss	I would be afraid of uncomfortable social situations on board such a bus	(Acheampong & Cugurullo, 2019; Backer-Grøndahl et al., 2007; Bansal et al., 2016; Hohenberger et al., 2016; Korkmaz et al., 2021; Nordhoff et al., 2019; Sener et al., 2019)

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Table 11 (*continued*)

MAVA-factor	Norwegian	English	Most relevant sources
Afraid of hacking (R) Safety/ Perceived risk/ Trust	Jeg ville vært redd for at noen kunne hacket datasystemet til bussen	I would be afraid that someone could hack the bus's data system	(Acheampong & Cugurullo, 2019; Backer-Grøndahl et al., 2007; Bansal et al., 2016; Korkmaz et al., 2021; Nordhoff et al., 2019; Sener et al., 2019)
Risky use (R) Safety/ Perceived risk/ Trust	Denne bussen ville være risikabel å ta i bruk	This bus would be risky to use	(Acheampong & Cugurullo, 2019; Backer-Grøndahl et al., 2007; Bansal et al., 2016; Korkmaz et al., 2021; Nordhoff et al., 2019; Sener et al., 2019)
Improve traffic safety Safety/ Perceived risk/ Trust	En sånn buss ville økt trafikksikkerheten	Such a bus would increase traffic safety	(Acheampong & Cugurullo, 2019; Korkmaz et al., 2021; Nordhoff et al., 2019; Raue et al., 2019; Xu et al., 2018)
Trust the bus Safety/ Perceived risk/ Trust	Jeg ville stolt på en sånn buss	I would trust such a bus	(Choi & Ji, 2015; Lee & See, 2004; Nordhoff et al., 2019)
Useful to me Service and vehicle characteristics/ perceived benefits/ performance expectancy	Jeg tror denne typen buss vil være nyttig for meg	I think this type of bus will be useful for me	(Acheampong & Cugurullo, 2019; Korkmaz et al., 2021; Nordhoff et al., 2019; Raue et al., 2019; Xu et al., 2018)
Nice design important Service and vehicle characteristics/ perceived benefits/ performance expectancy	Det er viktig at bussen har et fint design	It is important that the bus has a nice design	(Hohenberger et al., 2016; Kyriakidis et al., 2015; Sener et al., 2019)
Comfort important Service and vehicle characteristics/ perceived benefits/ performance expectancy	Det er viktig for meg at bussen er komfortabel	It is important to me that the bus is comfortable	(Hohenberger et al., 2016; Kyriakidis et al., 2015; Sener et al., 2019; Venkatesh et al., 2012)
Don't increase travel time Service and vehicle characteristics/ perceived benefits/ performance expectancy	Det er viktig at bussen ikke forlenger reisetiden min	It is important that the bus does not extend my travel time	(Hohenberger et al., 2016; Kyriakidis et al., 2015; Sener et al., 2019; Venkatesh et al., 2012)
Better than regular bus Service and vehicle characteristics/ perceived benefits/ performance expectancy	En sånn buss ville vært bedre enn en tradisjonell buss	Such a bus would be better than a traditional bus	(Korkmaz et al., 2021; Sener et al., 2019; Venkatesh et al., 2012)
Injunctive norm Social influence/ Norm	Jeg tror andre syns det er bra at jeg bruker en sånn buss	I think others would think it's good that I use such a bus	(Acheampong & Cugurullo, 2019; Ajzen, 1991; Korkmaz et al., 2021; Sener et al., 2019; Venkatesh et al., 2012)
Descriptive norm Social influence/ Norm	Jeg tror folk flest vil ønske å bruke en sånn buss	I think most people would want to use such a bus	(Acheampong & Cugurullo, 2019; Ajzen, 1991; Korkmaz et al., 2021; Sener et al., 2019; Venkatesh et al., 2012)
Would be entertaining	Å bruke en slik buss ville vært underholdende	Using such a bus would be entertaining	(Hohenberger et al., 2016; Kyriakidis et al., 2015; Sener et al., 2019)

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Table 11 (*continued*)

MAVA-factor	Norwegian	English	Most relevant sources
Hedonic motivation			
Use when available Behavioral intention	Jeg vil ta i bruk en sånn buss når de blir tilgjengelige	I would use such a bus when they become available	(Ajzen, 1991; Choi & Ji, 2015; Madigan et al., 2017; Raue et al., 2019; Venkatesh et al., 2012; Xu et al., 2018; Zhang et al., 2020, 2020)
Use if geographically available Behavioral intention	Jeg ville prøvd dette busstilbudet hvis det ble tilgjengelig der jeg bor	I would try this bus service if it became available where I live	
Not use even if available (R) Behavioral intention	Jeg vil ikke bruke busstilbudet selv om det blir tilgjengelig	I would not use the bus service even if it became available	

A.2. Scree plot and simulated Eigenvalues

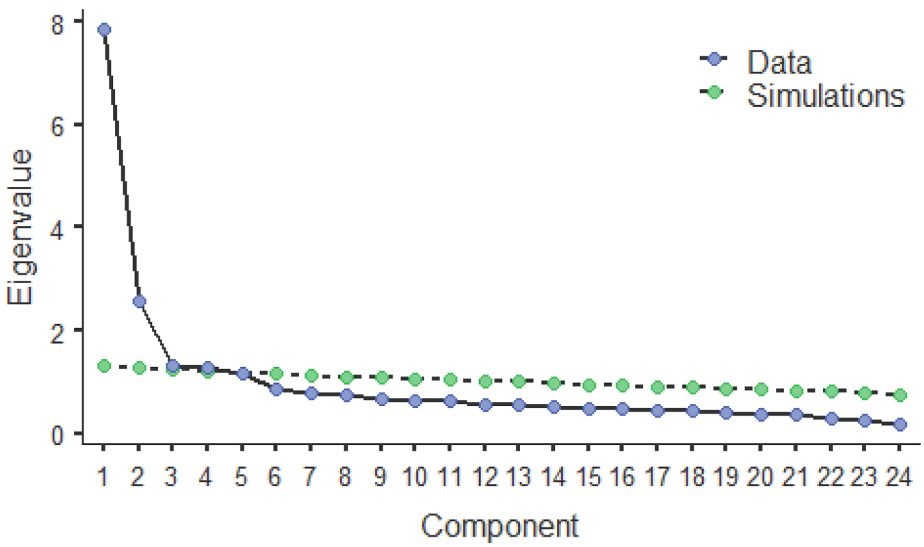

Fig. 3. Scree plot and simulated Eigenvalues are plotted.

A.3. Correlation matrix

Table X
Correlation matrix between study variables, N = 1902.

	Gender	Age	Income	Publictransport use	Tech-savviness	Exposure	PCA MAVA	PCA Interpersonal security	PCA Sociability
Age	−0.12***								
Income	−0.09***	−0.15***							
Public transport use	0.09***	−0.02	−0.02						
Tech-savviness	−0.37***	−0.06*	0.26***	−0.05*					
Exposure	−0.05*	−0.05*	0.08***	0.06*	0.15***				
PCA MAVA	−0.05*	−0.10***	0.15***	0.11***	0.31***	0.09***			
PCA Interpersonal security	0.02	−0.17***	0.07**	0.03	0.11***	0.04	0.19***		
PCA Sociability	0.01	−0.14***	−0.02	−0.03	−0.09***	−0.04	−0.45***	0.04	
Intention	−0.04	−0.07**	0.11***	0.14***	0.25***	0.06*	0.86***	0.18***	−0.41***

Note. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Data availability

Data is openly published

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