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# Norwegians' preferences for automated vehicles

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ABSTRACT

The present study predicts Norwegians' preferences for automated vehicles (AVs). We contribute to the state of the art of AV studies by identifying the relative importance of different predictors including demographic, socioeconomic, travel attributes, and psychological factors (i.e., the technology acceptance model (TAM), the theory of planned behaviour (TPB), personal innovativeness, and risk perception) in a Nordic country. A stratified random sample of Norwegians (n = 1000) was used as data in an artificial neural network. The findings show that (1) most people prefer partially AVs followed by high level AVs and conventional vehicles, (2) psychological factors have a greater influence on AV preferences compared to demographic, socioeconomic, and travel attributes, and (3) the five most important predictors of AV preferences are perceived ease of use of high level AVs (importance (i) = 100 %), subjective norm (i = 63.1 %), innovativeness (i = 59.9 %), attitudes towards high level AVs (i = 45.5 %), and perceived usefulness (i = 39.2 %). Policies and AV promotion could be based on components in the TAM and the TPB. Norwegians' personal beliefs and social norms regarding usefulness, efficiency, and ease of driving with high level AVs can to a large extent positively influence their preferences to use AVs with a high level of automatisation. Norwegians seem to be ready for a transition to high level AVs regardless of their age, gender, education, or income. This latter finding implies that AV promotion in Norway can rely on broad nudging strategies aimed at all licensed drivers, rather than targeting specific demographics.

## Introduction

One of the trending transitions in the mobility sector, heavily influenced by industry marketing, is the automation of vehicles and driving systems. It has been reported that Automated Vehicles (AVs) can bring several advantages to the transportation system such as less fuel consumption, greater safety, and a more efficient traffic flow (Fagnant & Kockelman, 2015; Wadud et al., 2016). Although often framed as a technological fix for transport challenges (e.g., safety, environmental issues), AVs may fall short in addressing systemic issues such as traffic congestion and car dependency. Despite these limitations, the automobile industry continues to employ strategic marketing to show AVs as solutions to mobility problems. In this study, we adopt a neutral stance on the broader sustainability implications of AVs, acknowledging the possibility of negative spillover effects (Mehdizadeh and Klöckner, 2024). Notably, this technology is more likely to gain traction in wealthier countries, where the financial and infrastructural capacity to support AV adoption is more readily available. Recognizing this disparity, we argue that a transition toward automated mobility centres on anticipating the levels of automation that individuals are likely to prefer in their future vehicles.

Although several previous studies have investigated correlates of intention to use a specific level of AV such as conditionally/partially automated, highly automated, or fully automated vehicles, little is known about people's preferences for using a vehicle from no automation level (conventional cars) up to a highly automated level. There is also less knowledge about AV preferences in the Nordic countries (i.e., Norway, Denmark, Sweden, Finland, Iceland) compared to other settings such as the US, the UK, Germany, and China. Nordic countries are renowned for their high electric vehicle uptake (Mersky et al., 2016). Despite an abundance of research regarding electric vehicle adoption in the Nordic countries, there is scant research on AV preferences. In other words, mobility transition in terms of automation has not been as well understood in this region compared to electric vehicle uptake. In

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Norway, for example, the electrification of vehicles has been quite successful, and Norwegians have demonstrated their openness to this type of mobility transition (Fevang et al., 2021; Mehdizadeh et al., 2024). This makes Norway an interesting case for studying another trending transition (AVs) in the mobility sector. Norwegians tend to use some electric vehicles, such as various Tesla models, providing some form of conditional or partially automated driving control. It is evident from this that Norwegians are indirectly involved in the automation transition as well.

Furthermore, driving conditions in Scandinavia, particularly in Norway, are different from those in other countries. Norway has many undivided two-lane roads. Speed limits are generally set at 80 km/h in sparsely populated rural areas and 50 km/h in urban/*peri*-urban areas with a somewhat dense population, but they can be lower depending on local road conditions. In terms of area, Norwegian territory is larger than British territory and has about the same size as Germany, but it has a much longer distance from north to south than the British and German territories. Besides distances, topography plays a significant role in Norwegian transportation.[2] With its numerous islands, deep fjords, steep mountains, glaciers, lakes, and long valleys, the landscape is unusually fragmented, especially around the coast. To cross fjords and reach islands, car ferries are commonly needed. Winter driving in Norway is also challenging, so handling a vehicle in such conditions is imperative, particularly on mountain roads. Snow and ice are common on Norwegian roads during the winter season, and Norwegians are accustomed to driving in heavy snowfalls. Handling the vehicle in slippery conditions is also an integral and mandatory part of driver training. During snowfall, traffic generally runs at a slower pace than normal.

In addition, past studies overlooked making more precise predictive models to reveal the relative importance of predictors. When it comes to psychological and behavioural research on AVs in particular, most studies are limited to explaining the associations between variables using statistical analyses. A more powerful predictive technique such as machine learning could be able to shed light on more accurate insights into the relative importance of different theories/predictors (Duan et al., 2022; Goetz et al., 2015). The findings of this study may reveal new insights about the degree to which Nordic countries with successful electrification transitions and unique driving conditions are prepared to transition to AVs. We also contribute to the state-of-the-art in AV studies by developing an Artificial Neural Network (ANN) to better predict preferences for three levels of vehicles namely conventional vehicles (no automatisation), partially AVs, and highly AVs. ANNs provide high predictive accuracy and allow for better optimization by examining both linear and non-linear relationships between dependent and independent variables (DeTienne & DeTienne, 2017; Leong et al., 2020). ANNs are also effective at handling discontinuities and nonlinear transformations, as well as identifying variables that contribute to and do not contribute to a solution. In addition, ANNs do not require prior model specification and statistical assumptions (e.g., multicollinearity, normal distribution of residuals) (DeTienne & DeTienne, 2017; Duan et al., 2022). We also explore the relative importance of psychological, demographic, socioeconomic, and travel attributes on AV preferences among Norwegians.

The society of automotive engineers (SAE) describes 6 levels of automation ranging from Level 0 (no automation) to Level 5 (fully automated) (Smith, 2013). Since fully automated (autonomous) vehicles were not commercialised in the real market of Norway, we investigated preferences from Level 0 to Level 4 in this study. As for the aim of better prediction, we convert five levels of the vehicles to the three following vehicles in ANN analysis: conventional car (Level 0), partially AVs (Levels 1 and 2), and highly AVs (Levels 3 and 4). As for the predictors, we consider the effect of factors from (1) risk perception theory, (2) the Technology Acceptance Model (TAM), (3) the Theory of Planned Behaviour (TPB), (4) innovativeness, (6) travel attributes alongside (5) demographic and socioeconomic variables explaining preferences for different automatisation levels of vehicles.

## A review of the literature

We mainly reviewed studies that investigated the acceptance of different levels of automated vehicles. The literature regarding automated vehicles and driving can be classified into different streams based on various standpoints.

As for the target level of AV, some studies only investigated the acceptance of fully automated vehicles (self-driving cars). As we are not going to consider fully automated vehicles in this study, we have only cited a few relevant studies on this topic, which we can use in shaping our study's theory. The rest of studies have examined the intention/tendency to use highly automated vehicles/driving and partially automated vehicles. As shown in Table 1, a number of studies have examined people's preferences for one specific AV, such as Level 2 (Hardman et al., 2019), Level 3 (Buckley et al., 2018; de Winter & Nordhoff, 2022; Liu et al., 2022; Merat et al., 2014; Nordhoff et al., 2020; Robertson et al., 2017; Zhang et al., 2019; Zhang et al., 2020), Level 4 (Dai et al., 2021), and Level 5 (Benleulmi & Blecker, 2017; Chen & Yan, 2018; Panagiotopoulos & Dimitrakopoulos, 2018). There is a gap in previous studies in that, except in one study, no study has investigated preferences for conventional cars (Level 0) as opposed to partly automated cars and different levels of AVs in one study.

As for the place of the study, most studies have been confined to the US, China, Germany, Australia, and a few Western European countries, respectively. Nordic countries, however, lack a comprehensive understanding of the preferences for Avs, which might be different from other regions due to extensive experience with EVs on the one hand, but specific road conditions on the other.

Regarding variables or theories used in past research, the most reported correlates/explanatory variables of AV preferences can be classified as follows.

(i) Through the lens of the TAM, Perceived Usefulness (PU) and Perceived Ease of Use (PEU) are the two main psychological factors explaining AV preferences in the literature. The TAM is a theory of information systems that aims to understand how users accept and use new technologies (Davis, 1989). According to the TAM, PU and PEU can influence the intention to use new technology. PU reflects how helpful a system (here AV) is perceived to be and therefore whether AV would improve driving efficiency or convenience (Buckley et al., 2018). PEU is a measure of whether an individual perceives that using an AV will reduce their exertion, thus perhaps a reduction in effort to drive using AV (Buckley et al., 2018). According to the literature, higher PEUs and PUs are positively associated with stronger intentions to use AV (Benleulmi & Blecker, 2017; Buckley et al., 2018; Karami et al., 2022; Panagiotopoulos & Dimitrakopoulos, 2018; Xu et al., 2018). The studies cited above also showed that the factors from the TAM had good explanatory power for AV usage intention.

(ii) According to previous studies and the TPB(Ajzen, 1991), favourable attitudes (ATT) towards using AVs, subjective norms (SN), and perceived behaviour control (PBC) are associated with greater intentions to use different AVs (Buckley et al., 2018; Chen & Yan, 2018; Dai et al., 2021; Karami et al., 2022; Liu et al., 2022). A person's attitude refers to the degree to which they endorse or disapprove of the behaviour of interest. Subjective norms refer to the belief about whether significant others approve or disapprove a particular behaviour. Perceived behavioural control refers to a person's perception of how easy or difficult it is to perform a certain behaviour.

(iii) Several risk perception factors regarding use of AVs have been found as a barrier towards intention to use AV in the future (Karami et al., 2022; Robertson et al., 2017; Tham et al., 2021;

[2] https://en.wikivoyage.org/wiki/Driving_in_Norway.

**Table 1**
An overview of the characteristics of past studies regarding the intention to use AVs.

| Study | SAE level | Place | Variables/Theory | Analysis |
|---|---|---|---|---|
| (Avetisyan et al., 2022) | L1, L2, L3 | USA | Trust, Workload, Satisfaction | Experimental |
| (Behnood et al., 2022) | L3, L4, L5 | USA | Opinions, Perceptions, Socioeconomic, Demographic, Car attributes, Region | Choice model |
| (Benleulmi & Blecker, 2017) | L5 | Germany | TAM, Social influence, Innovativeness, Convenience, motivation, Risks | Path analysis |
| (Buckley et al., 2018) | L3 | USA | TPB, TAM, Trust, Workload, Age, Sex | Experimental, Regression |
| (Chen & Yan, 2018) | L5 | Taiwan | TPB, Innovativeness, Price sensitivity, Perceived risk | SEM |
| (Cunningham et al., 2019) | L3, L4, L5 | Australia | Perceptions (benefits, concerns), Driving functions, Conditions, | Correlations |
| (Dai et al., 2021) | L4 | China | TPB, Trust, Satisfaction, Demographics | SEM |
| (de Winter & Nordhoff, 2022) | L3 | Several EU and non-EU countries* | The unified theory of acceptance and use of technology + hedonic motivation, price value, habit | Factor Analysis |
| (Du et al., 2022) | L2, L3, L4, L5 | China | Opinions (misconceptions) | Choice model |
| (Hardman et al., 2019) | L2 | USA | Attitudes, Household information, Vehicle information | Choice model |
| (Karami et al., 2022) | L0, L1, L2, L3, L4 | Iran | TPB, TAM, Risk, Habit, Resistance to change, Socioeconomic | Choice model |
| (Liu et al., 2022) | L3 | China | TPB, Social conformity, Innovativeness, Sex | Regression |
| (Nordhoff et al., 2020) | L3 | 8 EU countries | The unified theory of acceptance and use of technology | SEM |
| (Panagiotopoulos & Dimitrakopoulos, 2018) | L5 | Greece | TAM, Trust, Social influence | Regression |
| (Robertson et al., 2017) | L3 | Canada | Knowledge, Attitudes, Perceptions | Descriptive |
| (Tham et al., 2021) | L3, L4, L5 | Japan | Benefit and Risk Perceptions | SEM |
| (Wang et al., 2022) | n.s | USA | Demographic, Socioeconomic, Built environment, Travel needs | SEM |
| (Waung et al., 2021) | n.s | USA | Risk, Trust | Regressions |
| (Weigl et al., 2022) | L5 | Germany, USA | Desirability of control | Correlations |
| (Weigl et al., 2021) | L3, L5 | Germany | Drivers and Barriers of the adoption of automated driving | Path model |
| (Xu et al., 2018) | L3, L5 | China | TAM, Trust, Safety | Experimental, SEM |
| (Zhang et al., 2019) | L3 | China | TAM | SEM |
| (Zhang et al., 2020) | L3 | China | TAM, Trust, Sensation seeking, Social influence, Personality traits | SEM |

* Finland, France, Germany, Hungary, Italy, Sweden, Spain, UK, Brazil, China, India, Indonesia, Japan, Turkey, South Africa, USA.

Waung et al., 2021). Generally speaking, two main risk approaches including risk-as-analysis and risk-as-feelings have been reported as correlates of weaker AV preferences. Using reason, logic, and knowledge, the person tries to determine the source of risk in the first case (Nordfjærn et al., 2021). An instinctual and intuitive reaction to a risk source is the second case (Nordfjærn et al., 2021). In this way, rational and subjective assessments of risk can create or intensify emotions such as worry. In the risk-as-analysis, probability assessment and severity of consequences of an accident with AV are two main factors, while worry can belong to risk-as-feelings. For example, Karami et al. (2022) found that higher assessments of accident probability and worries negatively correlate with intention to drive highly automated vehicles. Additionally, it has been reported that different concerns can also influence people's preferences for AV. For example, Cunningham et al. (2019) pointed out that concerns about legal liability and data privacy could be related to AV preferences.

(iv) AV preferences may also be influenced by personal innovativeness. People with higher personal innovativeness have the tendency to try out new technologies earlier than others (Agarwal & Prasad, 1998). Individuals with strong innovativeness (those who are looking forward to new technologies) have reported stronger intentions to use AVs (Benleulmi & Blecker, 2017; Chen & Yan, 2018; Liu et al., 2022).

(v) Different demographic and socioeconomic attributes such as age, gender, education level, and income level have also been found to be correlated with AV preferences in previous studies (Buckley et al., 2018; Dai et al., 2021; Hardman et al., 2019; Karami et al., 2022; Liu et al., 2022; Wang et al., 2022).

A closer look at these findings shows that (i) there is less knowledge about AV preferences in the Nordic countries, and (ii) even though there is an agreement in positive or negative associations of the above cited variables on AV preferences, less knowledge exists about the relative importance of the variables/theories. Most studies have used statistical analyses and econometric models as analytical methods. While these analyses can reveal significant associations and directions of relationships, they are based on different assumptions that do not provide possible non-linear relationships and interaction effects that can be more appropriately modelled with machine learning techniques.[3]

To sum up, our aim is to fill the research gaps by predicting Norwegians' preferences for AVs using machine learning techniques. Since machine learning techniques do not require model pre-specifications, multicollinearity, and distributions checks, we consider potential variables as the input layer in the ANN. According to the reviewed literature,

[3] Statistical analyses, such as Structural Equation Models (SEM), investigate the relationships between variables and the explanation of a dependent variable, but (i) do not have predictive nature (almost descriptive/confirmatory nature based on theoretical frameworks), and (ii) provide less information about the relative importance of variables; therefore we classified them as having low predictability power. Our classification of choice models as of medium predictivity power is based on the fact that they give more options regarding sensitivity analysis and predictions compared to SEM. These theory-driven choice models, however, still rely on different labour-intensive search processes to capture interactions and/or nonlinearities (van Cranenburgh et al., 2022), which are most often ignored or hard to capture. Machine learning has several advantages over choice models. The first step in specifying choice models is to handcraft them somehow manually with linear utility functions and relatively few interactions. On the other hand, machine learning is based on complex functional forms and is completely data-driven. There is no need to decide about the model specification (Zhao et al., 2020). In a neural network, layers can be defined, and data drives the model towards its final specification. Model development with discrete choice involves incremental improvements, trial, and errors. The process of machine learning, however, is systematic (Bierlaire, 2019). The selection of models is also different. Statistical theory and hypothesis testing are used in choice models. In machine learning, out of sample validation is preferred. A training set is used to train the model, and a validation set contains data that was not used for training. A model's validity is determined by the quality of the predictions it makes on the validation set (Bierlaire, 2019).

the following 17 potential predictors will be tested in the input layer: (1) age, (2) gender, (3) education level, (4) income level, (5) EV ownership, (6) driving experience in kilometre, (7) driving experience in years, (8) PU, (9) PEU, (10) attitudes, (11) subjective norm, (12) perceived behaviour control, (13) innovativeness, (14) probability assessment of an accident while driving an AV, (15) severity of consequences, (16) worry, and (17) different concerns regarding using a highly AV.

## Method

### *Sampling*

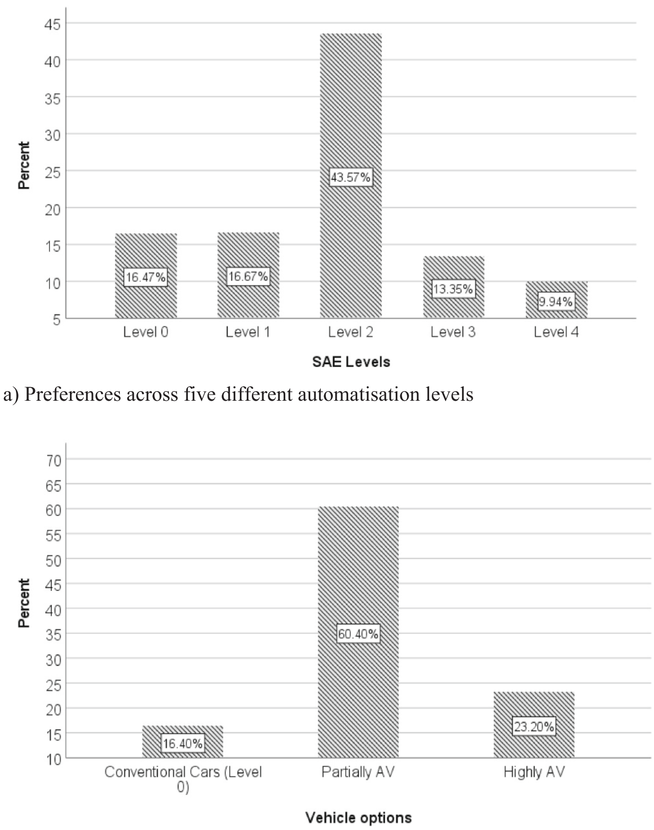
Using a random sampling technique from a survey panel, we selected 1000 Norwegians with driving licenses to participate in a self-reported online survey in November 2021. We stratified the survey participants based on region, age, and gender, and collected data from all 11 Norwegian counties. Survey participation was completely voluntary. Participants were informed of the confidentiality of their data. In this study, a few missing values were replaced by estimates using multiple imputation. 51 % of the sample was female and 7 % of respondents were between the ages of 18 and 22, 22 % between the ages of 23 and 35, 39 % between the ages of 36 and 55, and the rest were more than 55 years old. The sample characteristics are similar to those of the Norwegian population, according to Statistics Norway (2021). About 50 % of Norwegians above the age of 16 are female, which is almost exactly the same as our sample's female percentage. Our sample is also geographically distributed in line with Norwegian population statistics. For instance, 22.3 % of the Norwegian population lives in Viken, which is Norway's most populous county, which has the highest percentage of respondents in our sample.

### *Measures and descriptives*

This study was conducted as part of a larger survey to evaluate the progress of Norwegian mobility innovation. Several scales that have been validated were developed by Norwegian and English-speaking researchers and were translated for use in the survey, which was originally developed in English and developed by researchers proficient in both languages. As part of the survey, an explanation of AV (in a simple language) was also provided.

### *Dependent variable*

Preferences for different types of vehicles in terms of automation were the dependent variable. By one item, participants were asked which level of automation they in general would prefer in their future car. The initial measurements were based on a five-point scale starting at Level 0 (no automation) and ending at Level 4 (highly automated). Explanations for the various levels of AVs were provided in the survey as follows: In the hierarchy of driving automation levels outlined by the Society of Automotive Engineers (SAE), Level 4 is identified as "high automation". SAE levels 0 to 4 illustrate the progression of vehicle automation. Level 0 involves no automation, Level 1 provides driver assistance, Level 2 enables limited self-driving, Level 3 handles specific conditions autonomously with a standby driver, and Level 4 achieves high automation in predefined scenarios. Descriptive statistics show that 43 % of respondents would prefer Level 2 AVs (such as Tesla's current level of automation). To overcome the issue of low preferences at some levels, such as level 4, which could lead to a large extent of aggregation bias in predictions in the modelling process, we converted this scale into a nominal variable (with three categories). Level 0 responses are recorded as conventional vehicles (Level 0), Level 1 and Level 2 responses as partially AVs, and Level 3 and Level 4 responses as highly AVs. In Fig. 1.b, partially AVs, highly AVs, and conventional vehicles have 60.4 %, 23.2 %, and 16.4 % of the market share, respectively.




a) Preferences across five different automatisation levels

b) Preferences across three automatisation levels

**Fig. 1.** Frequency (percentage) of Norwegians' preferences for AVs in the sample (n = 1000).

### *Predictors*

Two sets of predictors were recorded in the survey. Firstly, psychological items were used to measure TAM, TPB, risk, and innovativeness factors. In the second part, demographic, socioeconomic and a few travel attributes were recorded. We also obtained each respondent's age, gender, education level, income level, EV ownership status, annual driving experience in kilometres, and driving experience in years.

To develop psychological measurement instruments, we targeted the highest level (i.e., level 4) of AVs. A tested and validated measure was used to evaluate the TAM factors (Buckley et al., 2018; Karami et al., 2022; Xu et al., 2018). Six statements were used to assess PU and PEU. Three items such as "highly AVs will be fuel efficient" were used to assess PU. Also, three statements such as "Learning to use a highly automated car will be difficult" were employed to measure PEU. The answers to these items were recorded with a five-point Likert scale from 1 to 5 (psychological questions and answer scales can be found in Appendix A).

We adapted different components of the TPB, including attitudes, subjective norms, and perceived behaviour control, based on existing scales (Chen & Yan, 2018; Dai et al., 2021; Karami et al., 2022). The TPB statements were slightly modified to reflect the highly AVs' adoption. A total of three items were used to assess attitude, including "using a highly automated car would be flexible". These items were rated on a five-point Likert scale from (1) "a lot more rigid" to (5) "a lot more flexible", (1) "a lot more boring" to (5) "a lot more enjoyable", and (1) "a lot more unpleasant" to (5) "a lot more pleasant" (see Appendix A). Three items such as "Other drivers would recommend me to use a highly automated car" were used to measure subjective norms. Perceived behaviour control was also assessed by three statements (e.g., "I have the necessary capabilities to use a highly automated car"). Both subjective norms and perceived behaviour control were rated on a five-point Likert scale ranging from (1) “strongly disagree” to (5) “strongly agree”.

The respondents reported their level of innovativeness by rating three items such as “If I heard about a new vehicle technology, I would look for ways to try it out” on a five-point Likert scale ranging from “strongly disagree” to “strongly agree”. This instrument has been tested and validated in past studies (Chen & Yan, 2018; Liu et al., 2022). A five-point Likert scale ranging from (1) “strongly disagree” to (5) “strongly agree” was used.

Perceived risk was assessed (i) as the probability of an accident while using a highly AV in comparison to driving a conventional car, (ii) as the severity of any accidents occurring while driving a highly AV in comparison to driving a conventional car, and (iii) as the level of worries about being involved in an accident when using a highly AV in comparison to driving a conventional car. Each of these three items were evaluated on a five-point Likert scale ranging from (1) “a lot lower” to (5) “a lot higher” for the probability assessment, (1) “a lot less severe” to a (5) “lot more severe” for the severity of consequences, and (1) “a lot less often” to (5) “a lot more often” for the worry. These items were tested and validated in a past study (Karami et al., 2022). In addition, nine different concerns about using highly AVs including “safety consequences of equipment or system failure”, “legal responsibility for drivers by accidents caused by equipment or system failure”, “system/vehicle security (e.g., from hackers)”, data privacy (e.g., location and destination tracking), “interacting with vehicles with low or no automation”, “interacting with other vehicles with the same levels of automation”, “interacting with pedestrians and bicyclists”, “system performance in poor weather”, and “the car getting confused by unexpected situations” were asked from participants. A five-point Likert scale ranging from (1) “not at all” to (5) “very” was used to evaluate the level of concerns. The means and standard deviations for these predictors can be found in Appendix B.

## ANN analysis

Since the aim of our study was to explore the relative importance of different predictors on AV preferences, we used an Artificial Neural Network (ANN) analysis. The ANN is a machine learning technique used to simulate the way human brains learn and process information (Leong et al., 2020). As illustrated in Fig. 2, a neutral network typically consists of three hierarchical layers: input, hidden, and output (Abiodun et al., 2018). The neurons of each layer are interconnected with those of the next layer.

As illustrated in Fig. 2, we used the feedforward backpropagation multilayer perceptron to quantify effects of factors *on* Norwegians’ AV preferences, where signals are fed forward from the input layer through the entire network to the output layer. As supervised networks, multilayer perceptron networks can be compared against known target variables to ensure the model-predicted results are accurate (Gardner & Dorling, 1998). Each neuron’s input is multiplied by its synaptic weights and summed, and this signal is transformed into its output by using a nonlinear activation function (Leong et al., 2020). A set of input neurons $X(X_1, X_2, X_3, \cdots, X_n)$ as predictors are contained in the input layer. A set of unobservable nodes, or units $Y(Y_1, Y_2, Y_3, \cdots, Y_j)$, make up the hidden layer. Predictors determine the value of each hidden unit. The weights of the input neuron $i(i = 1, 2, 3, \cdots, n)$ to the hidden neuron $j$ are represented by $W_{ji}$. Responses $O(O_1, O_2, O_3, \cdots, O_k)$, are contained in the output

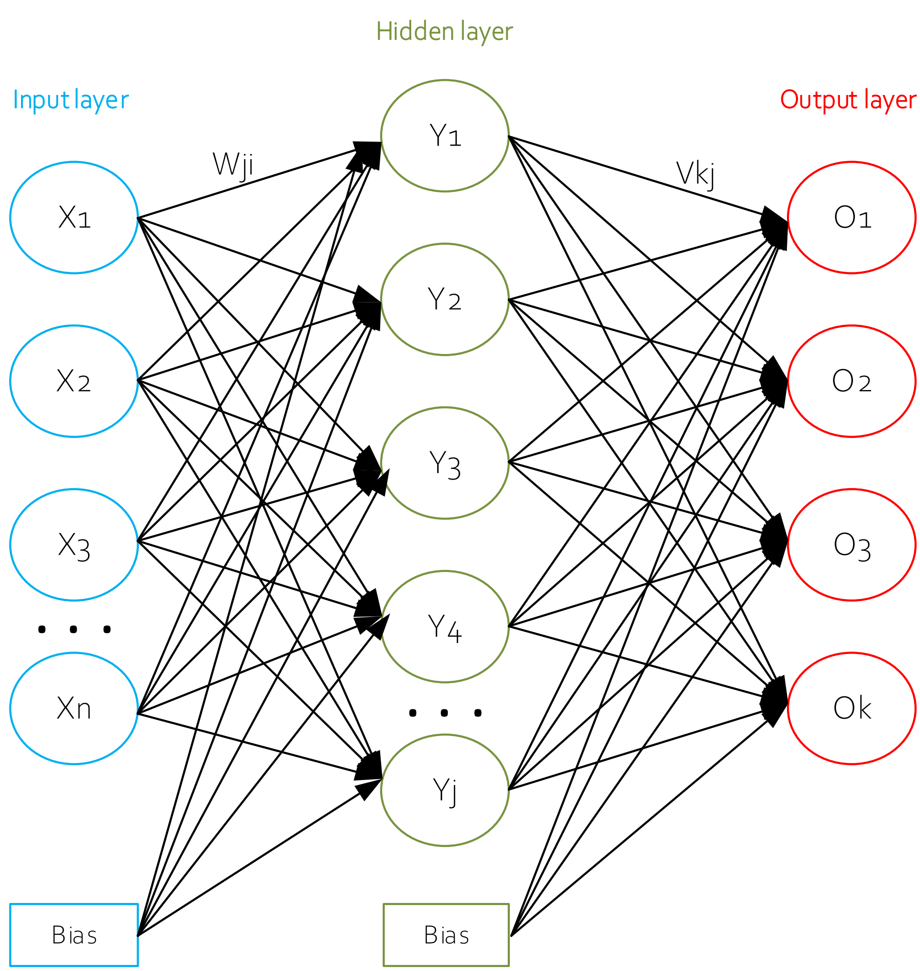



**Fig. 2.** The architecture of feedforward backpropagation multilayer perceptron network.

layer. Each output unit is a function of the hidden units. The weights of the hidden neuron $j$ to the output neuron $k(k = 1, 2, 3, \cdots, j)$ are represented by $V_{kj}$. In other words, the j-th hidden neuron can be expressed as follows:

$$net_j^h = \sum_{i=1}^{n+1} W_{ji}x_i + b \text{ and } y_j = f\left(net_j^h\right) \tag{1}$$

The k-th output neuron can also be expressed as:

$$net_k^o = \sum_{j=1}^{j+1} V_{kj}y_j + b \text{ and } o_k = f\left(net_k^o\right) \tag{2}$$

Different activation functions such as sigmoid, hyperbolic tangent, softmax were tested for the hidden and output layers, however, final functions with the least incorrect predictions were selected. The hyperbolic tangent (tanh) activation function with a parameter $\lambda$ is used for the hidden layer as follows:

$$f\left(net^h\right) = \frac{1}{1 + e^{-\lambda net^h}} \tag{3}$$

Compared to the sigmoid (logistic) function, the tanh function provides stronger gradients and big learning steps. Also, tanh is symmetric around zero leading to faster convergence. The softmax activation function was used for the output layer. Softmax activation functions are used when the output of the neural network is categorical. Softmax converts the linear output into a probabilistic one between 0 and 1, as follows:

$$f(net^o) = \frac{e^{-\beta net^o}}{\sum_{k=1}^{K} e^{-\beta net^o}} \tag{3}$$

In the learning process, an output pattern $o_k$ will be generated by the network according to an input pattern, which will then be matched to the desired response of every neuron $d_k$. Furthermore, the weights will also be altered at a later point in order to rectify or minimize the error that has been made, and then the subsequent pattern will be forwarded. For the output layer weights, V, the weight adjustment formula is computed as follows:

$$V_{kj}(t+1) = v_{kj}(t) + c\beta(d_k - o_k)o_k(1 - o_k)y_i(t) \tag{4}$$

For the hidden layer weights, W, the weight adjustment is computed as follows:

$$W_{ji}(t+1) = w_{ji}(t) + c\beta\lambda y_j(1 - y_j)x_i(t)\left(\sum_{k=1}^{K}(d_k - o_k)o_k(1 - o_k)v_{kj}\right) \tag{5}$$

where, for input pattern-p, $d_{pk}$ represents the desired output of neuron-k, whereas $o_{pk}$ represents the actual output of neuron-k (Venugopal et al., 2004). This process will be repeated until the cross-entropy error (CEE) across all training patterns is minimised.

The minimum sample size required by ANN for consistent and reliable predictions is 50 times the number of predictions or 10 times the number of attributes (Haykin, 2009). In this study, initially, 17 predicting attributes (aggregating 9 concern items into one predictor) are used to predict the dependent variable, with three predictions classes (conventional cars, partially AVs, and highly AVs) in the ANN model, requiring a minimum sample size of 850. To better assess the relative importance of specific concern items, we later included all 9 individual items as separate predictors in the model, resulting in a total of 25 predictors. The model fit for both versions (17 and 25 predictors) was comparable. Therefore, we proceeded with the ANN model that included all 25 predictors for a more detailed interpretation. It is worth noting that the concern items come from the same conceptual family and are inherently correlated. As such, we argue that including 9 related items does not introduce 9 entirely independent new predictors that would invalidate the sample size recommendation (850 vs. 1,250). The relative importance of the factors is measured by how much the predicted output value varies with different values of the independent variables. It is used in the sensitivity analysis to compute the normalised importance as the ratio of the relative importance of each variable with its highest relative importance and represented in percentage.

Cross-validation is used for computing ANN with 70 % of the data for training and 30 % for testing. To assess the predictive accuracy of the models, the cross-entropy error (CEE) and the percentage of incorrect predictions of both training and testing data sets for ANNs are used. The lower the value of CEE and the percentage of incorrect predictions, the better the predictive performance of the model (Duan et al., 2022).

## Analysis of results and discussion

The final structure of the developed ANN is shown in Fig. 3. The ANN has one hidden layer with eight hidden units (neurons). 25 predictors were entered in the input layer. Since the items related to each psychological factor (i.e., PEU, PU, ATT, SN, PBC, Innovativeness) have strong semantic similarity, the mean score of items was used as the value of each factor. As an example, the mean score of three innovativeness items was considered the value of innovativeness in the input layer. Since each of the probability assessments, severity of consequences, and worry variables from risk perception theory was evaluated with a single item, their scores were directly used as inputs in further analysis. Furthermore, as each of the nine concerns targets a specific concern, nine single concern items were used in the input layer. All variables were rescaled (i.e., standardised between −1 to 1) to improve network training. The results indicate that the model is reliable in capturing the relationship between the predictors and the dependent variable. Specifically, the overall percentage of correct prediction of AV preference model for both training and testing data is relatively high, with roughly equal values from 72.1 % and 72.0 %, respectively. Similar prediction power values show that the ANN model can offer high prediction accuracy and fit the data very well. Among three categories of the dependent variable, overall, 80.1 % and 82.3 % of the training and testing cases were classified correctly for partially AVs, corresponding to the 19.9 % and 17.7 % incorrect prediction in the model. Detailed estimations of the parameters can be found in Appendix C.

In Fig. 4, different indices of network performance are illustrated. As shown in Fig. 4.a, the predicted-by-observed chart displays clustered boxplots of predicted pseudo-probabilities for the combined training and testing samples. Observed response categories are on the x axis, and predicted response categories are on the legend. For example, the green box at the middle shows the predicted pseudo-probability of category partially AVs for cases with partially AVs observed. In general, this boxplot shows better prediction accuracy for partially AVs than for the other two categories.

Based on Fig. 4.b, the Receiver Operating Characteristic (ROC) curve shows all possible cut-offs' sensitivity and specificity. The area under the curve indicates, for each category, the probability that for a randomly chosen case within that category, the predicted pseudo-probability of being in that category will be higher than for a randomly chosen case outside that category. Area under the curves for conventional car, highly AVs, and partially AVs are 0.888, 0.861, and 0.752, respectively. This indicates that, for example, for a randomly selected respondent in highly AVs and a randomly selected case in conventional car, or partially AVs, there is a 0.861 probability that the model-predicted pseudo-probability of default will be higher for the respondent in partially AVs.

Based on a target percentage of the total number of cases, the cumulative gains chart shows the percentage of cases "gained" in a given category (Fig. 4. c). Suppose, for example, that the first point of the curve for partially AV cases is approximately at (10 %, 15 %). If we score a dataset with the network and sort all of the cases by predicted pseudo-probability of partially AV, we can expect that the top 10 % will contain approximately 15 % of all cases that qualify as partially AV. According to

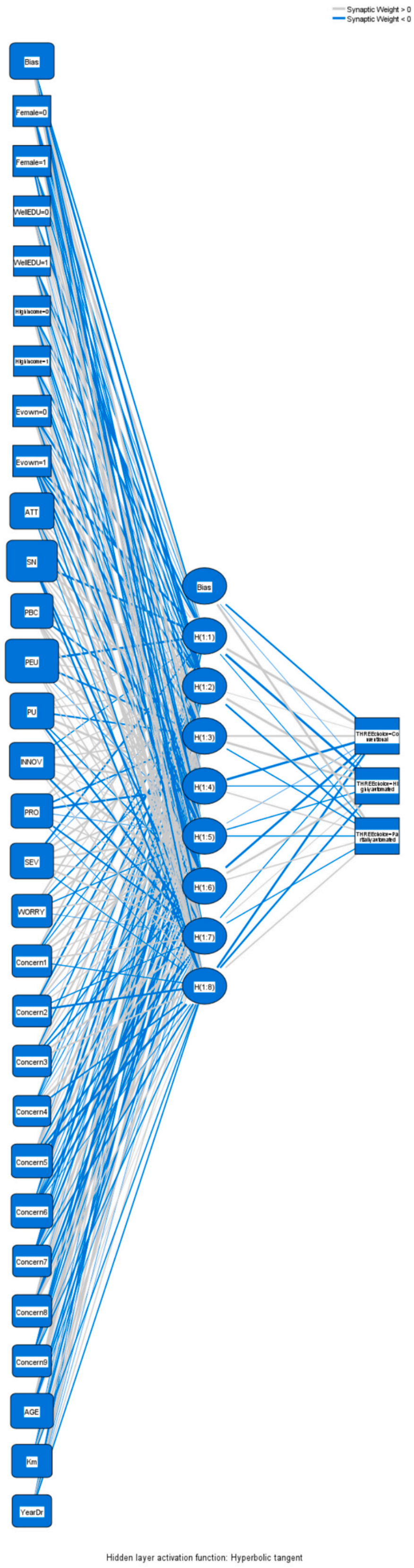



**Fig. 3.** The architecture of developed ANN.

this chart, partially AV categories show higher prediction accuracy than other categories.

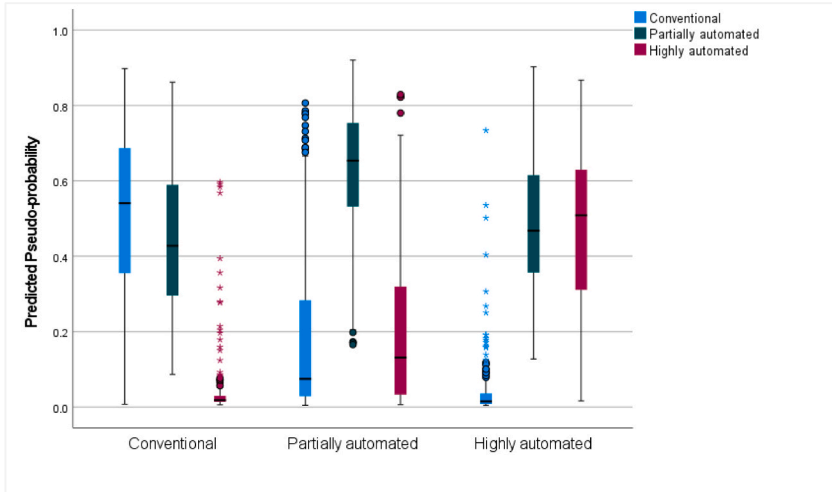
Each predictor's contribution to the preferences for different AVs was evaluated using sensitivity analysis. According to Fig. 5, we calculated the normalized importance in percentage terms based on the ratio of the relative importance of each input neuron divided by the absolute importance of the greatest input neuron. Based on the order of importance, the predictors of AV preferences among our Norwegian sample are perceived ease of use of highly AVs (PEU, 100 %), subjective norm towards highly AVs (SN, 85.7 %), innovativeness (INNOV, 54.0 %), attitudes towards highly AVs (ATT, 48.6 %), perceived usefulness of highly AVs (PU, 47.3 %), severity of consequences of an accident by a highly automated car in comparison to driving a conventional car (SEV, 43.7 %), age (40.2 %), perceived behaviour control (PBC, 38.4 %), perceived assessment of accident probability by a highly automated car in comparison to driving a conventional car (PRO, 35.8 %), concern about interacting with other vehicles with the same levels of automation (C6, 34.8 %), concern about interacting with vehicles with low or no automation (C5, 31.9 %), worry (28.1 %), driving experience in kilometre (Km, 27.2 %), concern of safety consequences of equipment or system failure (C1, 23.1 %), concern of system performance in poor weather (C8, 22.6 %), years of driving experience (YearDr, 22.0 %), concern of the car getting confused by unexpected situations (C9, 20.3 %), concern of legal responsibility for drivers by accidents caused by equipment or system failure (C2, 17.7 %), concern of interacting with pedestrians and bicyclists (C7, 17.6 %), concern about system/vehicle security (e.g., from hackers) (C3, 17.2 %), EV ownership (16.0 %), gender (13.6 %), concern about data privacy (e.g., location and destination tracking) (C4, 12.3 %), people with high income (8.9 %%), and high education (8 %).

These results highlight the important roles of psychological factors play for AV preferences compared to demographic, socioeconomic and travel attributes. As shown in Table 3, among the different sets of variables from psychological theories, the behavioural/attitudinal theory, including the theory of planned behaviour and the technology acceptance model, had the most important role in predicting AV preferences in this study followed by the concerns, risk perception, demographic and socioeconomic, innovativeness, and travel attributes.

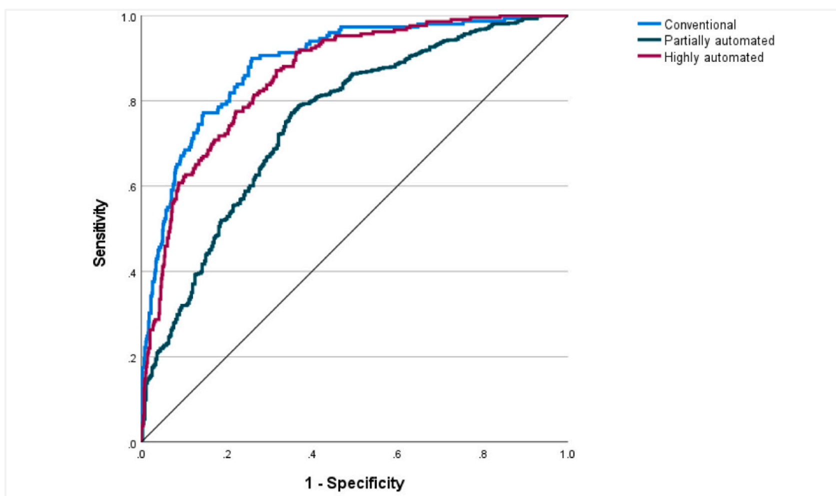
To explain the direction of relationship between different predictors and the dependent variable, the mean score AV categories was compared by the predictors in Fig. 6. For continuous (e.g., age) and scale (psychological factors) variables, the mean score is calculated, while for dummy/binary variables (e.g., gender, well educated people), the percentage of the reference category is calculated. These findings are discussed based on the order of importance of predictors. Our main comparison with the literature is in terms of the direction of relationships since the relative importance of predictors have not been studied previously.

Perceived ease of use (PEU) is the most important predictor of AV preferences and thus has normalised importance (i) of 100 %. However, the effect of PEU on AV preferences is non-linear, which non-linearity here means that the effect from level 0 to partially AV is stronger than on the step from partially AV to highly AV. A higher PEU of highly AVs is related to a higher AV choice. The latter finding is in agreement with previous studies in the USA, China, Greece, and Iran (Benleulmi & Blecker, 2017; Buckley et al., 2018; Karami et al., 2022; Panagiotopoulos & Dimitrakopoulos, 2018; Xu et al., 2018). Subjective norm, as the second most important predictor (i = 85.7 %), had a linear effect on AV preferences. Norwegians who perceive stronger social support for using a highly AV in their community are more likely to use a highly AV in the future. This finding is similar to those found in the USA (Buckley et al., 2018) and Taiwan (Chen & Yan, 2018), and contrary to those found in China (Dai et al., 2021) and Iran (Karami et al., 2022).

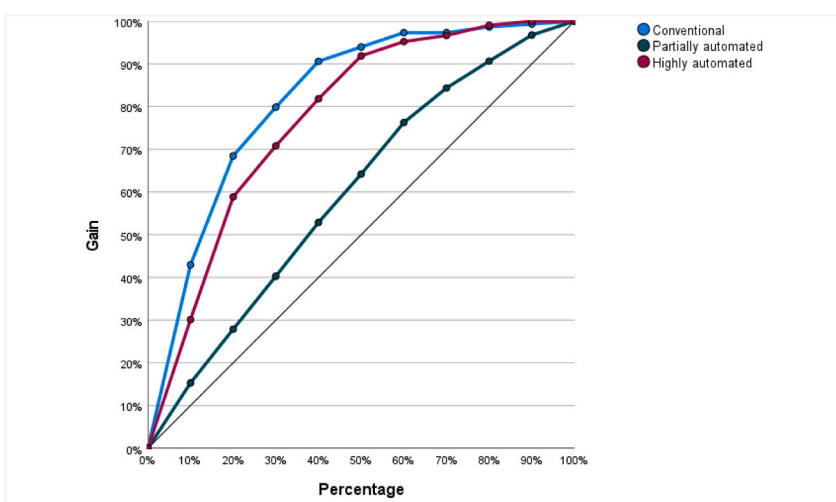
Innovativeness is the third most important predictor (i = 54.0 %) which had relatively linear effect on AV preference. People with higher personal innovativeness (e.g., those who are first to try out new vehicle




a) Predicted by observed chart




b) ROC (Receiver Operating Characteristic) curve




c) Cumulative gains chart

**Fig. 4.** Network performance based on the combined training and testing data.

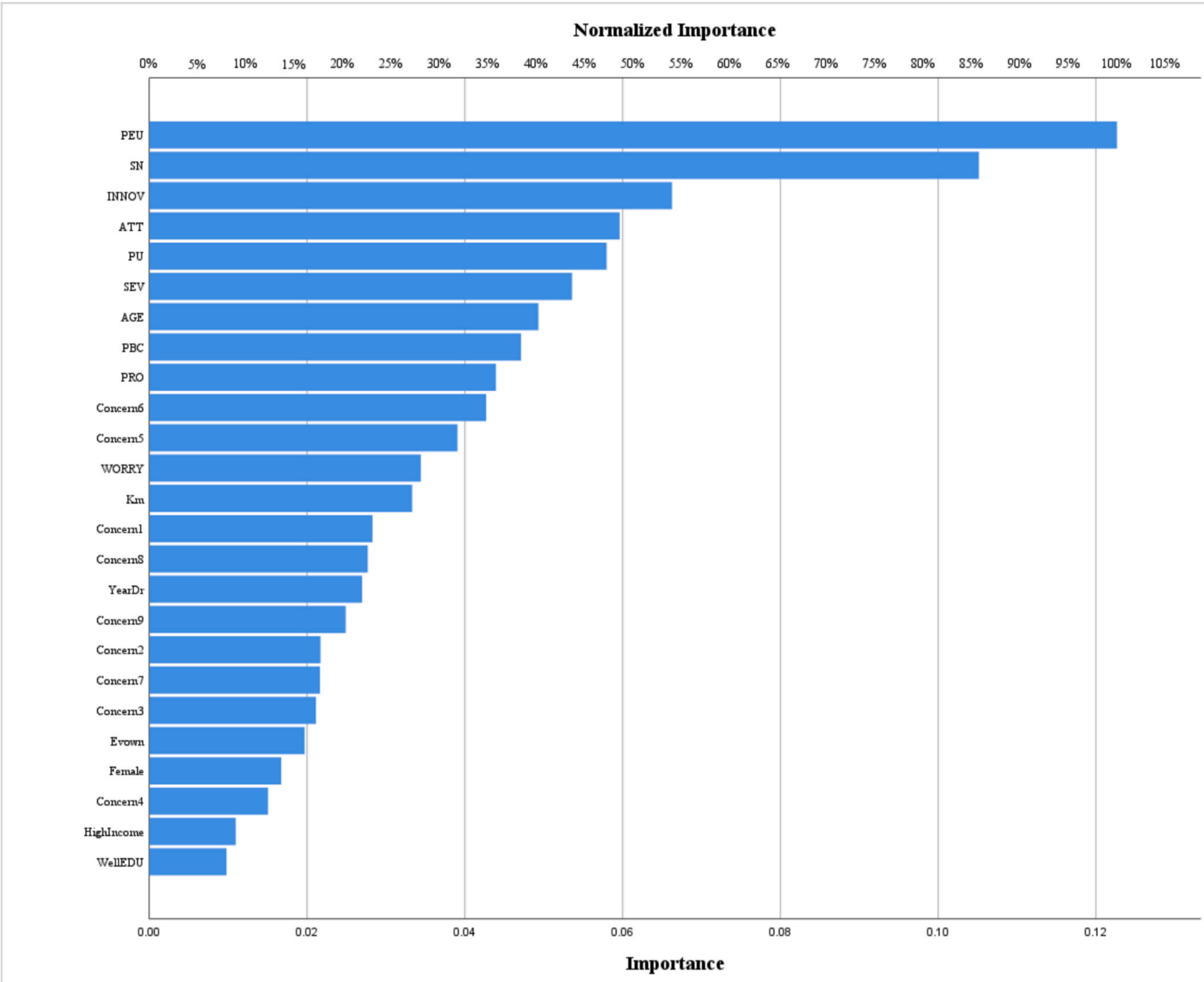



**Fig. 5.** The relative importance of predictors on AV preferences.

**Table 3**
The relative roles of different set of variables/theories on AV prediction.

| Set/Theory | | Sum of importance |
|---|---|---|
| Behavioural/ attitudinal | {TPB: 85.7 % (SN) + 48.6 % (ATT) + 38.4 % (PBC)} + {TAM: 100.0 % (PEU) + 47.3 % (PU)} | 320.1 % |
| Concerns | 34.8 % (C6) + 31.9 % (C5) + 23.1 % (C1) + 22.6 % (C8) + 20.3 % (C9) + 17.7 % (C2) + 17.6 % (C7) + 17.2 % (C3) + 12.3 % (C4) | 197.5 % |
| Risk Perception | 43.7 % (SEV) + 35.8 % (PRO) + 28.1 % (WORRY) | 107.6 % |
| Demographic and socioeconomic | 40.2 % (Age) + 16.0 % (EVown) + 13.6 % (Gender) 8.9 % (HighIncome) + 8 % (WellEDU) | 86.8 % |
| Innovativeness | 54.0 % (INNOV) | 54.0 % |
| Travel attributes | 27.2 % (Km) + 22.0 % (YearDr) | 49.2 % |

technologies among their peers) are more likely to prefer highly AVs. This finding is consistent with previous research in Germany, China, and Taiwan (Benleulmi & Blecker, 2017; Chen & Yan, 2018; Liu et al., 2022). Attitudes towards highly AVs as the fourth most important predictor (i = 48.6 %) had a relatively linear effect on the preferences of higher AVs. People who think that using highly AVs will be pleasant are more likely to use them in the future. This finding is an agreement with most previous research (Buckley et al., 2018; Du et al., 2022; Hardman et al., 2019; Liu et al., 2022; Robertson et al., 2017). Perceived usefulness (PU) as another factor of the TAM is the fifth most important predictor (i = 47.3 %), which had non-linear effect on AV preferences, meaning that PU makes more of a difference for the first difference (from level 0 to partially AV) than for the second (from partially AV to highly AV).

Interestingly, two main components of risk-as-analysis as safety measures of AV use were ranked among the sixth and ninth top predictors. It seems that working on beliefs (such as those related to the TAM and TPB constructs) can have a greater impact on the use of AV than safety interventions in Norway. Nevertheless, both accident involvement probability when using a highly AV in comparison to driving a conventional car (i = 35.8 %) and severity of consequences of such an accident (i = 43.7 %) had negative effects (relatively linear) on use of higher AVs. A higher risk perception regarding highly AVs is associated with a higher likelihood of a person still using conventional vehicles (Level 0). The same direction of relationship is also reported in previous research in the USA (Waung et al., 2021), Australia (Cunningham et al., 2019), Japan (Tham et al., 2021), Germany (Benleulmi & Blecker, 2017), and China (Xu et al., 2018).

Among the demographic and socioeconomic factors, age (i = 40.2 %)

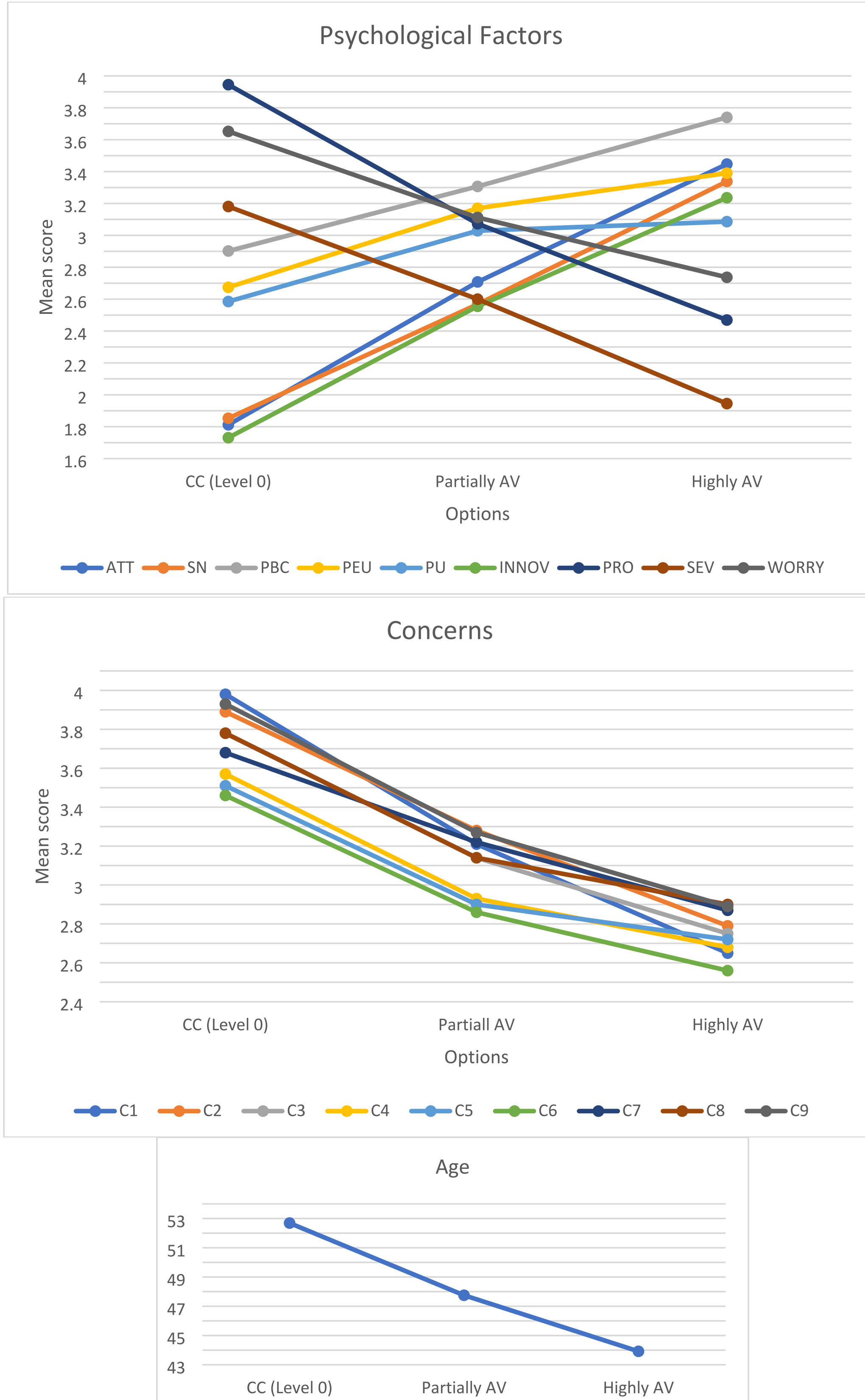



**Fig. 6.** Comparison of the means score of different AV options by predictors.

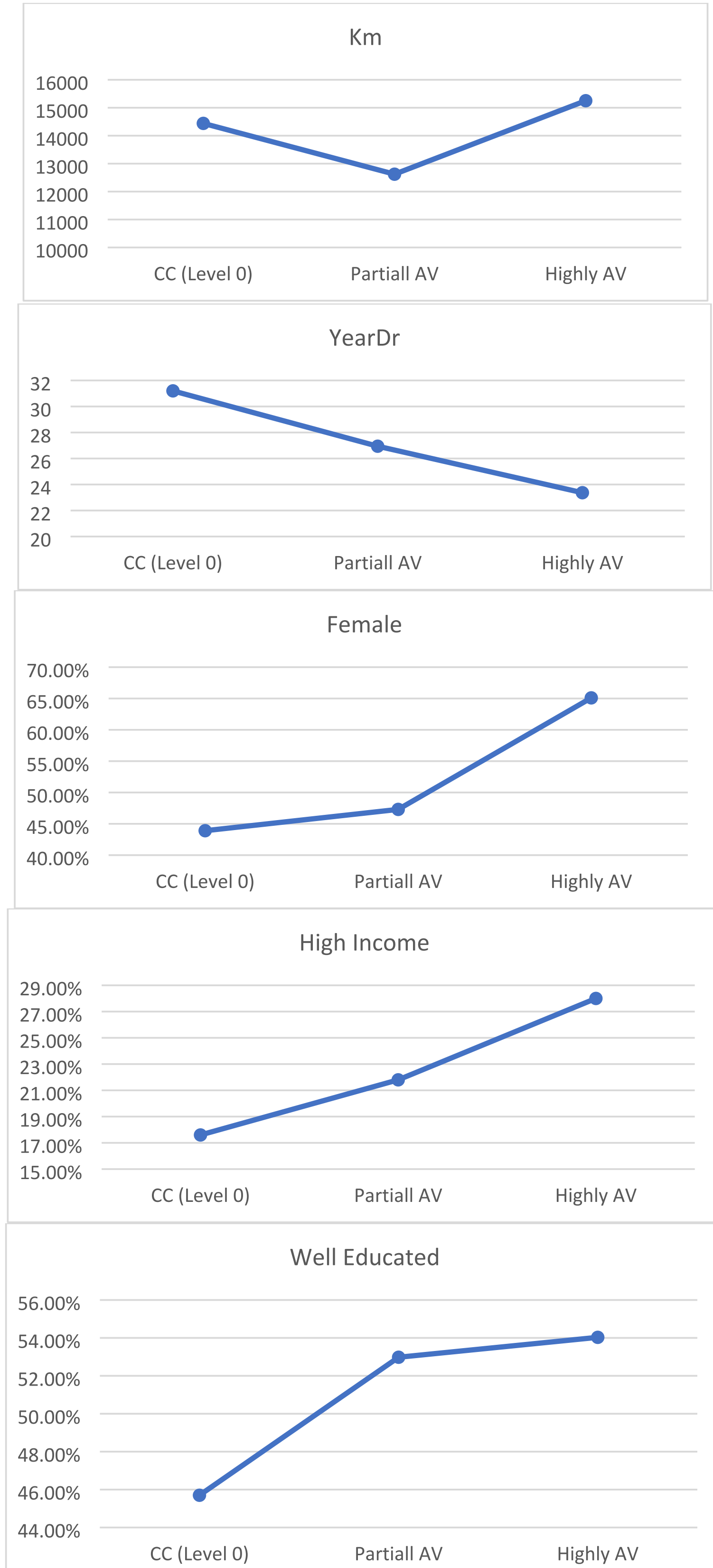



**Fig. 6.** (*continued*).

was the most important factor, and it was ranked 7th overall. The result shows that younger participants tend to prefer highly AVs compared to older participants. The average age of people who prefer conventional vehicles, partially AVs, and highly AVs is 53, 48, and 44 years, respectively. While two studies conducted in the USA (Buckley et al., 2018) and China (Dai et al., 2021) did not find a relationship between age and

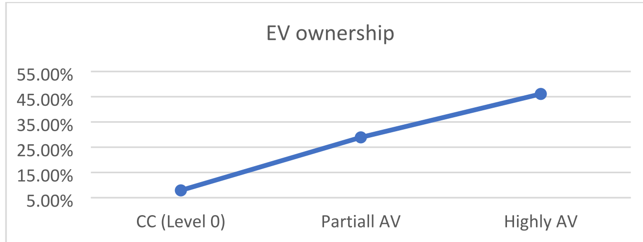



**Fig. 6.** (*continued*).

AV preferences, two other studies conducted in the USA (Hardman et al., 2019; Wang et al., 2022) did find that younger people are more likely to use higher AVs.

Among the behavioural/belief constructs, perceived behaviour control (PBC) had the weakest importance (i = 38.4 %) on AV preferences, and it was ranked 8th overall. There is a higher preference for highly AVs when PBC is high. The direction of this relationship is in line with most previous research (Buckley et al., 2018; Du et al., 2022; Hardman et al., 2019; Liu et al., 2022; Robertson et al., 2017).

Among the top ten predictors, concern regarding interacting with other vehicles with the same levels of automation was the 10th most important factor (i = 34.8 %) on AV preferences. Concern of interacting with vehicles with low or no automation was ranked as the 11th most important predictor. A negative relationship (relatively non-linear) was found between these concerns and high preferences for highly AVs. Worry as a risk-as-feelings factor was ranked 12th when it comes to the relative importance of predictors (i = 28.1 %). This result implies that risk-as-analysis factors (i.e., probability assessment and severity of consequences) have more important influence on AV choice compared to risk-as-feelings factors.

According to the ANN model, driving experience in kilometres (i = 27.2 %) and years of driving experience (i = 22.0 %) were the 13th and 16th top predictors of AV preferences. More experienced drivers in term of years of driving had stronger preferences for conventional vehicles compared to partially and highly AVs, which may highlight the role of resistance to change and conventional driving habits. However, travel mileage had no specific trend. People with higher driving mileages prefer highly AVs and conventional vehicles over partially AVs. Previous studies did not consider these factors.

The 14th and 15th most important predictors of AV preferences were two other concerns. Higher concerns regarding safety consequences of equipment or system failure (i = 23.1 %) and system performance in poor weather (i = 22.6 %) were negatively related to highly AV preferences. Moreover, four other concerns regarding using a highly AV including concern of the car getting confused by unexpected situations (i = 20.3 %), concern of legal responsibility for drivers by accidents caused by equipment or system failure (i =, 17.7 %), concern of interacting with pedestrians and bicyclists (i = 17.6 %), and concern about system/vehicle security (e.g., from hackers) (i = 17.2 %) were ranked 17th to 20th in importance in predicting AV preferences. The least important concern was data privacy (e.g., location and destination tracking) (i = 12.3 %), which may indicate high levels of Norwegians' trust in authorities.

Demographic and socioeconomic factors had weaker influences on AV preferences compared to psychological factors. The next variable was EV ownership status (i = 13.3 %) which had a relatively linear effect on AV preferences. The result shows that people who own an EV are more likely to prefer highly AVs. This finding is consistent with a recent study conducted in the USA (Behnood et al., 2022) that suggested electric vehicles are associated with AV preferences. Gender (i = 13.6 %) as the 22nd most important predictor had a non-linear effect on AV preferences. Although the effect of gender is negligible, the percentage of Norwegians' females in the highly AV group is higher than Norwegians' males. This finding contradicts the findings of two studies in the USA (Hardman et al., 2019; Wang et al., 2022) that found males are more likely to use AVs than females. Norwegians score very low (8) on masculinity compared to the United States (62) (Hofstede, 1998). We speculate that the traditional association between masculinity and travel behaviour may be less salient in a more feminine and egalitarian society like Norway. The least important predictors of AV preferences were income (i = 8.9 %) and education (i = 8.0 %) status. Both people with high education and income are more likely to prefer highly AVs.

## Conclusions

With the help of a machine learning technique, we predicted Norwegians' preferences for AVs. This technique allowed us to reveal the relative importance of different factors on these preferences. Unlike most previous research which only focussed on direction and correlation of variables on AV choice, we employed an ANN to provide higher predictive accuracy and allow for better optimisation by examining both linear and non-linear relationships as well as identifying variables that contribute to and do not contribute to a solution. Most Norwegians prefer partially AVs followed by highly AVs and conventional vehicles.

This work can have policy and practice implications. We found that psychological factors have greater influence on AV preferences compared to demographic and socioeconomic variables. Conventional statistical and econometric models could lead to misleading policies. For example, a recent study which mainly focussed on demographic, socioeconomic and built environment factors strongly highlighted the role of demographic and socioeconomic factors in policy and practice of AV promotion based on descriptive SEM analysis (Wang et al., 2022). However, our findings based on a machine learning technique revealed that demographic and socioeconomic factors have weaker importance compared to psychological factors. Furthermore, most previous research which focussed on psychological factors were not able to identify the relative impact of such factors on AV choices. According to the findings of the present study, policies and AV promotion campaigns could be developed on the basis of the technology acceptance model and the theory of planned behaviour. Norwegians' personal beliefs and social norms regarding usefulness, efficiency, and ease of driving with highly AVs to a large extent can positively influence their preferences to use highly AVs in the future. Norwegians concerns and risk perception regarding highly AVs seem to have weaker impacts on their decisions compared to their favourable attitudes towards AVs. This implies that risk perception campaigns may not be as important as attitudinal change campaigns when it comes to AV promotion in Norway. Norwegians seem to be ready for a transition to highly AVs regardless of their age, gender, education, or income. In accordance with these findings, AV promotion in Norway can rely on broad nudging strategies aimed at all licensed drivers, rather than targeting specific demographics. This latter finding has important policy implications, as it suggests that in wealthier countries like those in Scandinavia, if policymakers fail to critically assess the negative spillover effects of AVs on the transport system, the industry may be able to promote and normalize this technology on a broad scale with less effort, as demographic-specific marketing would not be necessary. A limitation of this study is that we did not ask participants about their prior experience with or knowledge of AV technologies. This may influence preferences, especially among EV owners who may be more familiar with partial automation. Future research should consider this factor.

## Statements and declarations

The corresponding author was affiliated with the Norwegian University of Science and Technology (NTNU) at the time of the initial submission; however, he was affiliated with the University of Leeds at the time of the revision submission. The project was funded by Norway through NTNU.

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## CRediT authorship contribution statement

**Milad Mehdizadeh:** Conceptualization, Formal analysis, Investigation, Methodology, Software, Writing – original draft. **Trond Nordfjærn:** Writing – review & editing. **Christian A. Klöckner:** Writing – review & editing.

## Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: The corresponding author was affiliated with the Norwegian University of Science and Technology (NTNU) at the time of the initial submission; however, he was affiliated with the University of Leeds at the time of the revision submission. The project was supported by Research Council of Norway (project nr: 296205).

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trip.2025.101493.

## Data availability

The authors do not have permission to share data.

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