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The role of psychological factors on the choice of different driving controls: On manual, partial, and highly automated controls

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ABSTRACT

The present study investigates the role of psychological factors on the choice of three controls (modes) in driving a vehicle, namely highly automated, partially automated, and manual control. Traditional driving habits, resistance to change, and behavioural beliefs were all assessed along with individual and socioeconomic variables. Using survey data (n = 595) of car users, a model was developed to predict the share of different driving controls and determine the effects of psychological variables. Results indicate that up to 55% of people prefer driving with highly automated control, and 30% prefer partially automated control. Behavioural beliefs (e.g., attitudes toward highly automated control) are not as critical to driving control as habits. People with stronger driving habits are less likely to use highly automated controls. A one-unit increase in worry could reduce driving in highly automated control by 5.5% and increase manual control by 4.5%, and those who welcome the new technologies are more likely to prefer highly automated control. Some practical policy solutions are also provided.

1. Introduction

Automated vehicles are considered a revolution in the transportation system, and are a highly anticipated technology for the coming decades. In many developed countries, arrangements are being made to incorporate these vehicles into their transportation systems. While automated vehicles are being produced and disseminated rapidly, human understanding of how they are used remains controversial. According to a global survey from 109 countries (Kyriakidis et al., 2015), which investigated user acceptance, concerns, and willingness-to-pay for different levels of driving controls, manual driving was reported as the most enjoyable driving mode by participants. There are many populated countries in developing regions that have a high desire for conventional vehicles (manual driving). It is unknown why people are still hesitant to use automated driving systems. For example, Iran is the 18th most populous nation worldwide with 82 million inhabitants (The World Bank, 2019). However, <10% of Iranians use automated driving[1].

Although many studies have been conducted in recent years that analysed the purchase/choice of autonomous vehicles (AVs) instead of conventional vehicles (e.g., see Gkartzonikas and Gkritza, (2019) for a thorough review), little is known about preferences for different driving controls. A number of different barriers and incentives, such as safety, distrust, convenience, and usefulness, have been reported in the use of AVs versus conventional vehicles (e.g., Kyriakidis et al., 2015; Panagiotopoulos and Dimitrakopoulos, 2018;

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Bansal et al., 2016; Haboucha et al., 2017; Ipsos MORI, 2014).

Many tech enthusiasts believe that using and promoting automated driving can improve traffic flow efficiency and reduce energy consumption (Wadud et al., 2016; Fagnant and Kockelman, 2015; NHTSA, 2016). On the other hand, human behavioural change versus their resistance to change, distrust of highly automated vehicles, as well as beliefs and risk perceptions, may lead to the formation of different levels of automation. Who still prefers a manual driving control? What about partially or highly automated driving control? Are driving habits with conventional vehicles and resistance to change influencing people's choices? Do favourable beliefs about automated driving and such technologies influence people's decision to choose automated driving controls? And, if so, what is its competitive role? These are unanswered questions addressed in the study.

The current study investigates psychological predictors of three driving controls named manual, partial automated, and highly automated controls. As this study aims to examine driving controls in a vehicle that can switch between automated and manual control, the autonomous/self-driving mode (Level 5) is not included. The society of automotive engineers (SAE) represents 6 levels of automation ranging from Level 0 to Level 5 (Smith, 2013)[2]. In the present study, level 0, which is considered the "manual control," assumes that human drivers are to perform all driving tasks. Human drivers generally monitor the road environment at levels 1–2, which are considered to be "partial control". At level 1, the driver and system share steering and acceleration/deceleration, while at level 2, the system does both steering and acceleration/deceleration simultaneously. Additionally, levels 3–4, referred to as "highly automated control" in the present research, represent that the system monitors the roadway environment and performs all dynamic driving tasks. While at Level 3, a driver will react and he or she is responsible for the request to intervene with the vehicle, at Level 4, this responsibility is relieved (Chaloupka and Risser, 2019).

1.1. A review of the literature

Despite extensive research on the psychological factors affecting the use of a specific level of automation (i.e., fully or highly automated) of automated vehicles (Chen and Yan, 2019; Choi and Ji, 2015; Ha et al., 2020; Nastjuk et al., 2020; Wang et al., 2021), little is known about why people prefer manual driving versus different levels of automation. In the context of the diffusion of fully automated vehicles, partial and highly automated driving controls represent pre-development stages, so it is important to identify the factors that influence the choice between manual and different levels of automation.

As for studies carried out on highly automated control, Xu et al. (2018) developed a psychological model to investigate factors affecting willingness to re-use a highly automated vehicle. They found that experience of using a highly automated vehicle will likely increase trust, perceived safety, perceived usefulness, and intention to re-use a highly automated control. Employing the unified theory of acceptance and use of technology (UTAUT), Madigan et al. (2017) tested public acceptance of highly automated vehicles (SAE level 4). They showed that the UTAUT framework can be used to maximise the acceptance of such automated vehicles. Applying the theory of planned behaviour (TPB) and the technology acceptance model (TAM), Buckley et al. (2018) reported that the TAM and TPB factors accounted for 41% and 46% of the explained variance on intention to use a highly automated vehicle, respectively. Employing survey data from China, Zhang et. al. (2020) revealed that intention to use highly automated vehicles can be explained by the TAM constructs, trust, social influence, and personality traits. They demonstrated that social influence and initial trust have important roles in explaining intention. Zhang et al. (2019) also added perceived privacy risk and safety risk to the TAM to study user acceptance of highly automated control. They found that perceived safety risk negatively affected acceptance of highly automated controls.

Among studies related to partial automation, most have addressed trust in the technology (Abraham et al., 2017), the intention to use these controls under different roads, weather and traffic conditions (Hardman et al., 2019), the learning process (Abraham et al., 2018), and the relevance of perceived usefulness and attitudes (May et al., 2017). For example, May et al., (2017) revealed that the intention to use partially automated driving is determined by attitudes, perceived usefulness, compatibility, and external variables such as tech experience, driving confidence, and driving enjoyment. Furthermore, they found that compatibility affects perceptions of usefulness and attitudes, which in turn lead to having a strong impact on behavioural intentions to use partially automated controls.

2. Research goals

Many studies have been conducted on the acceptance or behavioural intention of different levels of automation, but the state-of-the-art field still suffers from deficiencies. A closer look at the literature reveals that (i) most previous research has focused on the role of psychological factors on intention to use a fully automated vehicle (Chen and Yan. 2019; Choi and Ji. 2015; Ha et al., 2020; Nastjuk et al., 2020; Wang et al., 2021), (ii) applying a pre-planned (deliberate) behavioural framework such as the TPB and the TAM, studies mostly examined the role of beliefs (e.g. attitudes, perceived usefulness) on intention to use a certain level of automation. Furthermore, such studies failed to account for driving habits in conventional vehicles and resistance to change behaviour. Many traffic psychologists believe that in addition to favourable attitudes towards behaviour, our past behaviour (habit) and resistance to change can also impact our behaviour (Aarts et al., 1998; Verplanken and Orbell, 2003; Şimşekoğlu et al., 2015). It would be interesting to know which psychological concepts have a greater influence on the choice of different driving controls. On one hand, habits of manual driving coupled with resistance to change, and on the other, the pre-planned decisions (TPB and TAM) regarding highly automated driving?

[2] We converted the levels of control to three categories of manual control (Level 0), partial control (Level 1–2), and highly automated control (Level 3–4) to make choice options easily distinguishable. As a driver cannot drive manually in fully automated vehicles (Level 5), we did not consider this type of automation in the choice set.

The purpose of this study is to investigate the competitive effects of these factors on the choice of three levels of driving controls.

In most cases, people who are strongly interested in driving or who are more sensitive to risk may still choose to drive a vehicle manually (no automation) or partially automated. Hence, understanding which groups of people are most likely to use a vehicle for (1) High automation, (2) Partial automation, and (3) Manual control can help in better planning of the future transportation system and a more accurate estimation of the impacts of automation on mobility. In the present study, in a hypothetical situation, the respondents were asked if they are the owner of a vehicle with various options from manual to highly automated, which of the categories of the abovementioned driving control would they prefer most of the time? Additionally, finding the answer to this question can indirectly reveal people's interest in purchasing different levels of automation on the market.

Our research goal is to investigate the relative roles of the habit, resistance to change and deliberate planning about using highly automated driving on the preference of three driving controls (i.e., manual, partial automation, and highly automated). On such preferences, we also examine the role of perceived risks and worries. Utilising related psychological theories, the present study seeks to fill the research gaps. Various theories have been developed regarding the intention to perform certain behaviours. Since the present study tries to adapt people to a new driving mode with vehicles and to discourage them from the old (manual) driving performance, the most relevant behavioural theories were tested in the study. The following section reviews the research hypotheses and the conceptual framework of the study.

2.1. *Theoretical background and hypotheses*

2.1.1. *Theory of planned behaviour*

In the theory of planned behaviour (TPB) (Ajzen, 1991), it is postulated that behavioural intention may be pre-planned and explained by three main components: attitudes, subjective norms, and perceived behavioural control. Here, attitudes refer to the positive or negative evaluation of the individual towards the behaviour under study. The subjective norm reflects society's beliefs (especially important people in a person's life) about the behaviour under study. Perceived behaviour control refers to a person's perception of how easy or how difficult it is to perform the desired behaviour. The interaction of these three dimensions may lead to the formation of behavioural intention. The TPB has been investigated in various transportation studies, such as travel mode choice (e.g., Zavareh et al., 2020; Noblet et al., 2014; Nordfjærn et al., 2014a) and the behavioural intention of using AVs instead of conventional vehicles (e.g., Buckley et al., 2018; Chen and Yan, 2019; Moták et al., 2017; Sener and Zmud, 2019). For instance, Buckley et al. (2018) found that all three main components of the TPB significantly influenced the intention to use automated vehicles (Level 3). Therefore, our first hypothesis is formulated as follows.

H_1: We hypothesise that positive attitudes, subjective norms, and perceived behavioural control regarding highly automated control can positively influence behavioural intentions of highly automated control, while negatively affecting other driving controls.

2.1.2. *Technology acceptance model*

The Technology Acceptance Model (TAM) has been developed to explain people's acceptance of a new technology or information system (Davis, 1989). This theory consists of two main components of beliefs: Perceived Usefulness (PU) and Perceived Ease of Use (PEU). Perceived usefulness indicates the extent to which the use of a particular technology improves a person's performance in the task at hand. On the other hand, perceived ease of use shows to what extent the use of a particular technology can facilitate doing the task at hand. According to this theory, both of these components can directly affect behavioural intention.

In the literature, many studies have tested the behavioural intention of using AVs through the TAM (e.g., Wu et al., 2019; Lee et al., 2019; Zhang et al., 2019; Panagiotopoulos and Dimitrakopoulos, 2018; Xu et al., 2018). For instance, Xu et al. (2018) reported that, although PU was positively associated with the intention to use AVs, PEU was only positively associated with the intention to reuse AV after the actual first use. Panagiotopoulos and Dimitrakopoulos (2018) showed that both PEU and PU components significantly affect the intention to use AV, and PU had the largest effect among different variables. The second hypothesis of the study is stated as follows.

H_2: It is hypothesised that favourable PEU and PU toward using highly automated control can be positively related to using highly automated control and negatively associated with other driving controls.

2.1.3. *Driving habits and resistance to change*

Various debates in transportation have sought to determine whether driving is a routine process or deliberate cognitive processing (or both) (Nordfjærn et al., 2014a; Bamberg and Schmidt, 2003; Gärling and Axhausen, 2003). In the present study, in addition to examining the TPB as a deliberate planning behaviour, the role of traditional (manual) driving habits in driving control with automated modes would be tested for the first time. Psychological studies show that past behaviours can also be powerful leverage for shaping future behaviours (Aarts et al., 1998; Verplanken and Orbell, 2003; Şimşekoğlu et al., 2015). Therefore, frequent driving in today's life may lead to the habit of driving and spark people's interest in using manual rather than automated control in using a vehicle in the future. Previous studies also reported that people who have stronger driving or car use habit are more likely to continue their driving frequency and less likely to switch to other mobility modes (Gärling & Axhausen, 2003; Chen & Chao, 2011; Nordfjærn et al., 2014a; Şimşekoğlu et al., 2015; Friedrichsmeier et al., 2013). Hence, the following hypothesis is formulated.

H_3: We hypothesise that driving habits can increase the desirability of using manual control of a vehicle and decrease the desirability of using automated driving controls.

Further, whether a person's intention to drive with manual or automatic controls is affected by their resistance to change. Attempts to promote new behaviour (e.g., automated driving instead of manual driving control) may evoke psychological resistance (Tertoolen et al., 1998). People may resist behavioural changes in their lives for several reasons (Oreg, 2003). First, many people perceive changes

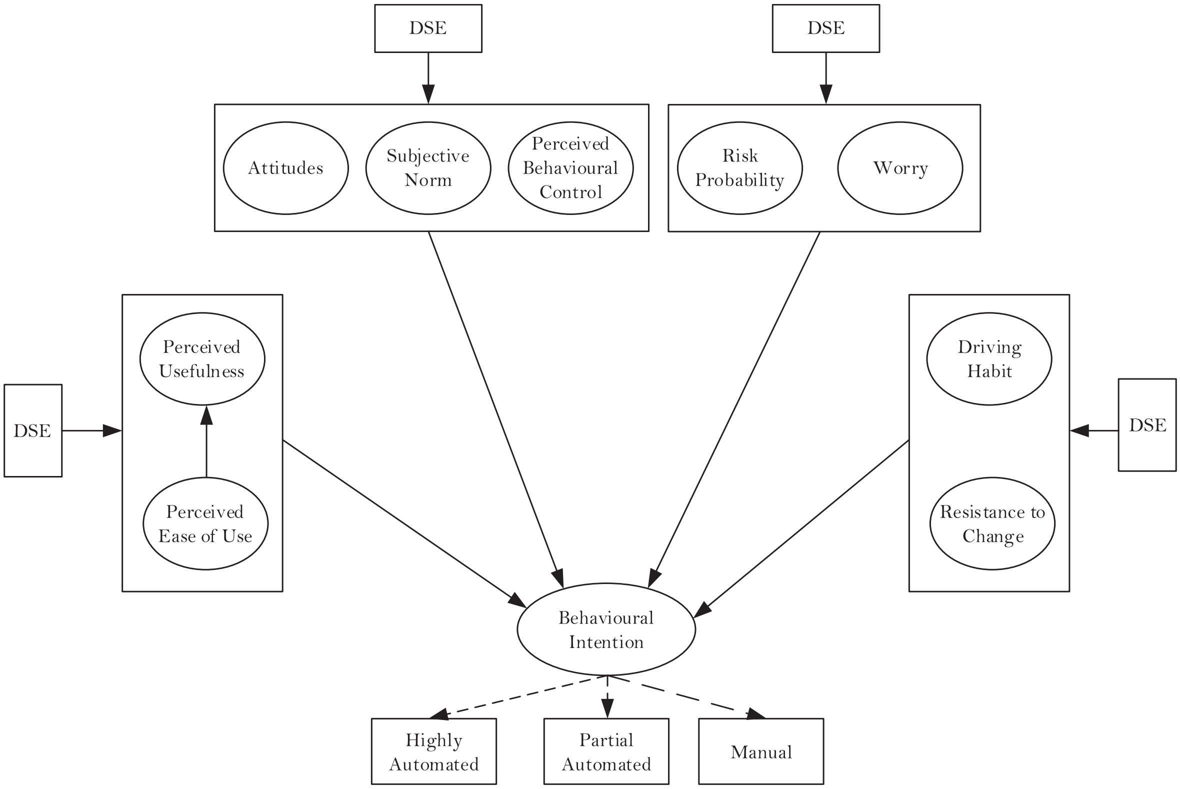


Fig. 1. Conceptual modelling framework of the study.

as negative. As opposed to trying out new and modern things, they prefer to do the same old things. Second, they may feel stressed if they have to change their plans. This issue implies an emotional reaction to a change. Third, many people have less flexibility when thinking about long-term plans, even if a change will enhance their quality of life. Fourth, some individuals are too rigid to change their views over time. Indeed, they cannot conveniently change their minds. For example, a person who has a strong habit of driving a conventional vehicle may be unwilling to use a highly automated control system, especially if they have a negative perception of the change. To date, no study has been carried out to investigate the effect of resistance to change and the use of vehicles in automated and manual controls. Hence, we formulated the following hypothesis.

H_4: We hypothesise that stronger resistance to change behaviour increases the desirability of using manual control and decreases the probability of using other driving controls.

2.1.4. Risk perception

Risk perception can be defined as "risk-as-analysis" and "risk-as-feelings" (Loewenstein et al., 2001; Slovic et al., 2013; Rundmo and Nordfjærn, 2017; Backer-Grøndahl and Fyhri, 2009). The first case is a process, in which the person tries to assess the source of risk based on reason, logic, and knowledge. The second case refers to intuitive and instinctive reactions to a source of risk. Thus, emotions such as worry, and anxiety can be formed or intensified as a result of rational and subjective assessment of risk. In transportation, risk perception is usually defined as the subjective assessment of the probability of an accident occurring and the severity of that accident (Backer-Grøndahl and Fyhri, 2009). In the field of driving behaviour, many studies have examined the relationship between risk perception and high-risk driving behaviours (Nordfjærn et al., 2011; Şimşekoğlu et al., 2012; Steinbakk et al., 2019), such as high speed. For instance, some studies have shown that perceptions of higher traffic risk are negatively correlated with the high speed of driving (Şimşekoğlu et al., 2012). Furthermore, studies have shown that risk perception can be a significant factor in choosing different transportation modes (Mehdizadeh et al., 2017; Nordfjærn et al., 2014b). For example, Mehdizadeh et al. (2017) showed that higher risk perception regarding walking and cycling increases the likelihood of choosing motorised transportation modes for travelling (e.g., using a car to go to school instead of walking/cycling). Regarding worries, Mehdizadeh and Ermagun (2020) found that stronger worries about walking increase the probability of exclusive use of car. In contrast, some studies showed that individuals were less worried about being involved in an accident when using active transport modes compared with car (Moen and Rundmo, 2006; Oltedal and Rundmo, 2007). Backer-Grøndahl et al. (2009) also reported that respondents had stronger worries regarding being in an accident than unpleasant incidents when using private travel modes while they reflected more worries about security issues on public transport. Accordingly, we developed our hypotheses as follows.

H_{5a}: It is hypothesised that a higher perceived risk of an accident occurring in the case of high automated control, decreases the desirability of using highly automated control and increases the desirability of using other driving controls.

H_{5b}: It is hypothesised that a higher perceived risk of an accident occurring in the case of manual control, decreases the desirability of using manual control and increases the desirability of using other driving controls.

H_{5c}: It is hypothesised that a higher feeling of worry in the case of highly automated control, decreases the desirability of using highly automated control and increases the desirability of using other driving controls.

H_{5d}: It is hypothesised that a higher feeling of worry in the case of manual control, decreases the desirability of using manual control and increases the desirability of using other driving controls.

2.2. Conceptual model of the study

According to Fig. 1, the conceptual model of the present study consists of four main theoretical sections as psychological predictors of different driving controls of a vehicle. Therefore, the study's main hypothesis is to examine the direct relationship between the psychological variables of the four main parts of the study with different driving modes of a vehicle. In other words, the model of the present study compares the competitive and direct effects of psychological variables on different levels of driving controls. Besides, demographic and socioeconomic (DSE) variables (such as age, gender, income, and level of education) were included in the modelling framework as control variables, correlating with psychological variables. Individuals with different demographic and socioeconomic attributes might have different psychological characteristics. Such control variables allow us to find better policies related to psychological traits among different segments of people.

As our conceptual modelling framework of the present study consists of different psychological theories (including latent variables and structural relationships) and three discrete driving modes, a Hybrid Choice Model (HCM) is developed. The HCM can be viewed as an expanded discrete choice modelling framework, which integrates different types of models into a single structure that is estimated simultaneously. The HCM allows the analyst to simultaneously test the effects of latent and manifest variables on the choice of different discrete alternatives (Ben-Akiva et al., 2002; Walker, 2001). In contrast to structural equation models, HCM allows us to perform a sensitivity analysis of different variables. Since our main aim was to understand the relative (and direct) roles of different "beliefs" and "habits/resistance to change" on the utility of choosing three options of driving controls, we did not consider a theory as a basis and contextualise the theoretical framework by adding relevant constructs.

3. Method

3.1. Sample

A sample of conventional car users in Tehran in February and March 2019 were recruited. A total of 22 car washes and parking lots in the 22 districts of Tehran were selected as the survey site, and the drivers of cars waiting for their cars to be washed or parked were asked to participate in the survey. Participation in this survey was entirely voluntary, and the respondents were assured that the questionnaire was confidential and the results would only be used for research purposes. Before starting to answer the questionnaire, the purpose of the survey was explained to all respondents, and since the information regarding different levels of automation in Iran was limited, the survey assistants explained about the automated vehicles and the different controls of driving them for three minutes. Fifteen survey assistants (transportation students) were trained to conduct a face-to-face survey. Furthermore, schematically, the levels of car options in three categories of manual, partially automated, and highly automated control were shown to the respondents. Besides, to ensure that the respondents are not confused about different levels of automation, they were allowed to ask some questions about different levels of automation options. Of note, the differences among different controls of a vehicle have also been introduced in the questionnaire.

In total, 710 car users at polling stations were asked to participate in the survey, of which 622 volunteered to participate (88% participation in the survey). After refining the data, 595 valid samples were considered for further analysis.

3.2. Questionnaire

The questionnaire of this study has different sections that include the general characteristics of the respondent, a hypothetical question about the driving controls, demographic and socioeconomic characteristics of individuals, driving habits, risk perception, and standardised measurement tools of psychological theories, including the TPB, and the TAM.

In the first part of the questionnaire, demographic characteristics (including age and gender), socioeconomic characteristics of individuals, including education, employment status, number of household members, number of owned conventional vehicles, and income status were recorded.

In a hypothetical question, respondents were asked about driving control preferences. They were asked: "Suppose you own a vehicle in the future that has all the driving options from manual to highly automated control, considering the features of each driving control (explained by the survey assistants), which driving control are you going to use the most (more than 50% of the time)"? Three levels of manual, partially automated, and highly automated control were offered as three answer options. According to the SAE's taxonomy of vehicle automation (Smith, 2013), the driving characteristics of "Level 0″ were assumed as manual, while either "Level 1″ or "Level 2″ was considered partial control. In addition, the driving features of "Level 3″ and "Level 4″ were assumed as highly automation control.

The components of the TPB were measured through a standardised and modified version of previous instruments (Ajzen, 1991;

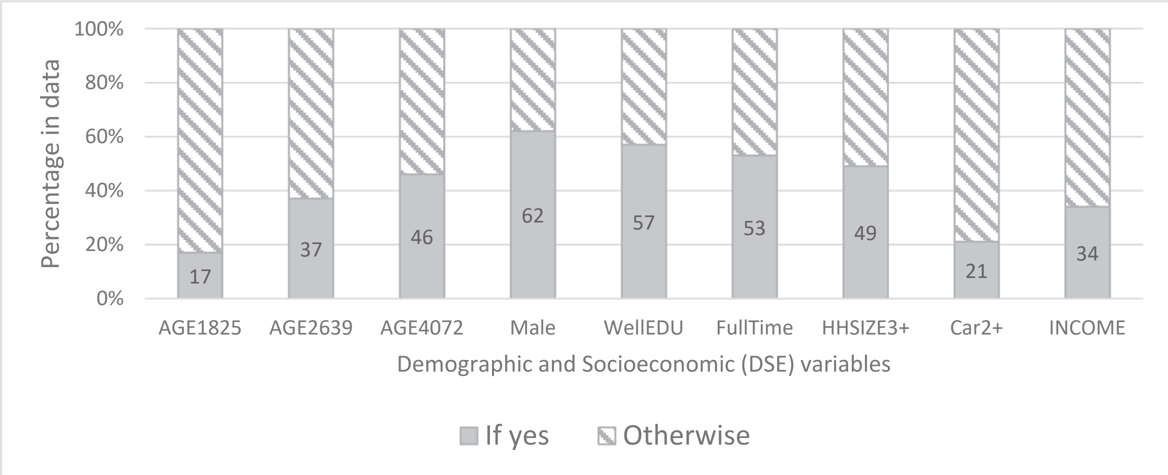


Fig. 2. Profiles of demographic and socioeconomic variables in dummy form.

Buckley et al., 2018; Chen and Yan, 2019; Moták et al., 2017). This instrument contains nine items to cover Attitudes (ATT), Subjective Norm (SN), and Perceived Behaviour Control (PBC) components. It should be noted that behavioural intention was measured as the final dependent variable by asking the abovementioned hypothetical question about driving control. These items were scored on a 5-point Likert scale ranging from (1) strongly disagree to (5) strongly agree. This tool contains four items for measuring attitudes, such as "For me driving a vehicle in high-automatic control would be: harmful/beneficial". Subjective norm was measured by three items, such as "I think people who are important to me want me to drive a vehicle in high-automatic control". The PBC component was measured by two items, such as "For me to drive a vehicle in high-automatic control in future would be: very difficult/very easy".

Tested tools from previous studies were used to measure the two main components of the TAM (Wu et al., 2019; Lee et al., 2019; Zhang et al., 2019; Panagiotopoulos and Dimitrakopoulos, 2018; Xu et al., 2018). Further, the items were slightly modified to match the components with the research question. Four items measured the PU component such as, "I think driving a vehicle in high-automatic control can make my driving easier", and another four other items evaluated the PEU component such as "I think driving a vehicle in high-automatic control is easy to learn".

Risk perception was assessed as the probability of an accident while using a vehicle's highly automated and manual control in urban and rural roads. A 5-point Likert scale from (1) very low to (5) very high was used. This tool contains items such as, "How probable do you think it is that you personally would be involved in an accident in urban roads when using the highly automated control?" In addition, the level of worry in the highly automated and manual control of a vehicle was measured on a 5-point Likert scale from (1) very low to (5) very high, which have been similarly tested and evaluated in previous studies in the field of transportation (Rundmo and Nordfjærn, 2017; Mehdizadeh et al., 2017; Nordfjærn et al., 2014b). This tool contains items, such as "How worried do you become when thinking about the risk of getting involved in an accident in urban roads when using the highly automated control?".

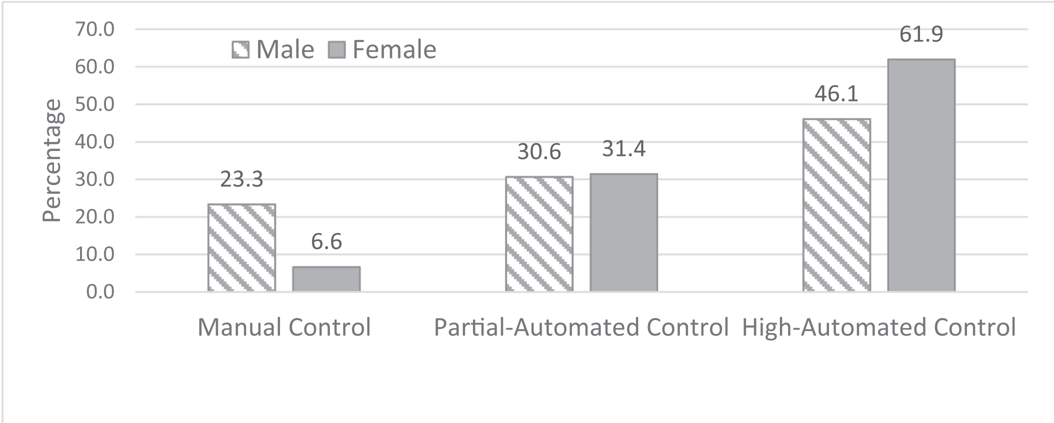
Driving habits were measured by standardised instruments of previous studies (Nordfjærn et al., 2014a; Verplanken and Orbell, 2003). A modified self-reported indicator of habit, including 12 items, such as "Driving is what I do most of the time" and "Driving is something I do without thinking" was used to measure driving habit. The instrument used a 5-point Likert scale from (1) strongly disagree to (5) strongly agree, in which higher numbers show stronger habits.

Furthermore, resistance to change was measured through a standardised and tested 19-item instrument (Oreg, 2003; Nordfjærn et al., 2014a). These items measure how people are willing to change or resist change concerning a particular behaviour. This tool contains items, such as "I generally consider changes to be a negative thing" and "I like to do the same old things rather than try new and different ones". Oreg (2003) found that these tools are divided into the following four factors: emotional reaction (how emotionally distressed one is by changes), routine seeking (avoiding innovation and being comfortable with routine life), cognitive rigidity (stability in the way you look over time), and short-term focus (resisting the changes that can be beneficial in the long-term). The degree of disagreement or agreement of individuals with each sentence was recorded on a 5-point Likert scale ranging from (1) strongly disagree to (5) strongly agree.

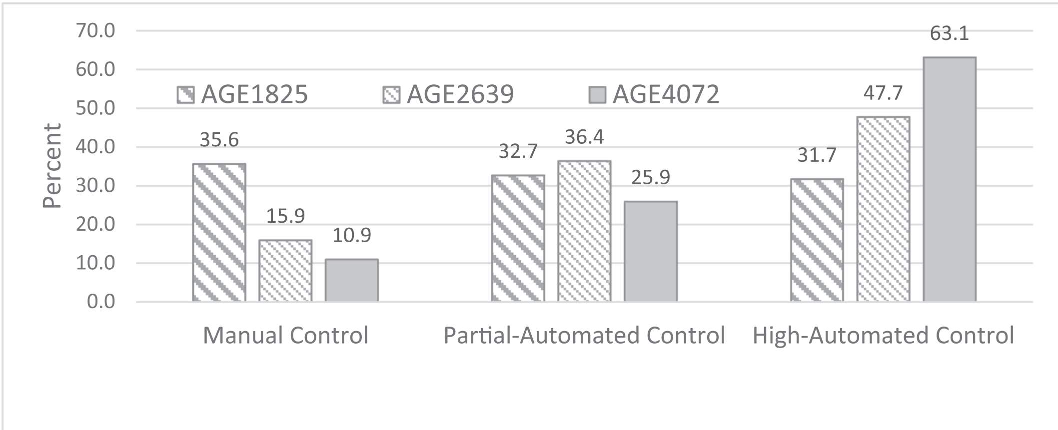
3.3. Sample characteristics

Five hundred ninety-five participants of the study consisted of 62% male and 38% female. According to Fig. 2, 17% were in the age group of 18 to 25 years, 37% in the age group of 26 to 39 years, and the rest in 40 years and above. In terms of educational status, 43% of people reported undergraduate, and the rest were graduate and above.

Regarding the driving control, 310 people (52%) reported that they intended to use highly automated control most of the time, 184 people (31%) intended to use a vehicle in partially automated control. The remaining (17%) reported the intention to use the manual control most of the time when driving a vehicle.



a) On gender



b) On age groups

Fig. 3. Driving controls by gender and age groups.

A closer look at the data shows that 23.3% of men tend to drive a vehicle in manual control, while only 6.6% of women reported such a tendency. The tendency of men and women to drive in highly automated control is 46.1% and 61.9%, respectively (Fig. 3.a). Besides, according to Fig. 3.b, the share of driving in highly automated control between the groups of young (18 to 25), adults (26 to 39), and mid-age (40 and above) is equal to 31.7%, 47.7%, and 63.1%, respectively.

The mean and standard deviation of different psychological items are provided in Table 1. For instance, among the components of the TPB, the highest mean values belong to attitude items.

4. Modelling approach

The HCM model was used to test the conceptual model, as illustrated in Fig. 1. In the HCM model, the simultaneous effects of latent and manifest variables on the dependent variable (choice behaviour) are tested (Ben-Akiva et al., 2002; Walker, 2001). This model consists of two main parts: the latent variable and the discrete choice model. The latent variable model itself includes measurement and structural models. In the discrete choice model, the effect of all latent and manifest variables is estimated simultaneously. Before testing the hybrid choice model, the measurement models of some behavioural theories for the formation of latent factors by their indicators were tested separately through factor analysis. Three factors of the TPB and four factors of resistance to change theory were confirmed through Confirmatory Factor Analysis (CFA) and were entered into the next modelling phase. Besides, two factors of the TAM, four factors of risk perception, and one factor of driving habit index, were explored by Principal Component Analysis (PCA) and entered the next phase (Jolliffe, 2002). Well-known indicators, such as RMSEA, TLI, and CFI, were used to test the accuracy and fit of CFA (Kline, 2015). RMSEA values are$<$0.05, TLI values are between 0.90 and 0.95, and CFI indicates a good fit of the measurement model (Kline, 2015). Besides, orthogonal rotation and repetition were used in PCA, and the factor loading of items below 0.4 was removed from the corresponding component. Except for a few items, other items were eligible to appear in their respective components. Moreover, all factors had acceptable Cronbach's alpha values (Alpha greater than 0.7). Then, the whole measurement model was established (CFA), including all latent constructs at the same time before developing the whole HCM. In the next step, the hybrid model of latent variable and discrete choice was developed. According to Fig. 1, the utility function of choosing three driving controls

Table 1
Descriptive of psychological items.

Items	Mean	SD
TPB		
Attitudes (ATT) (α = 0.86)		
ATT1. For me, driving a vehicle in highly-automatic control would be: harmful/beneficial.	3.56	0.99
ATT2. For me, driving a vehicle in highly-automatic control would be: unpleasant/pleasant.	3.51	0.87
ATT3. For me, driving a vehicle in highly-automatic control would be: bad/good.	3.64	1.01
ATT4. For me, driving a vehicle in highly-automatic control would be: not acceptable/acceptable.	3.50	0.96
Subjective Norm (SN) (α = 0.84)		
SN1. I think, people who are important to me, want me to drive a vehicle in highly-automatic control.	2.87	0.86
SN2. I think, people who are important to me, think I should not/ I should drive a vehicle in highly-automatic control.	2.82	0.95
SN3. People who are important to me, approve/disapprove of me driving a vehicle in highly-automatic control.	2.79	0.91
Perceived Behavioural Control (PBC) (α = 0.79)		
PBC1. For me to drive a vehicle in highly-automatic control in future would be: very difficult/very easy.	3.22	0.95
PBC2. How confident are you that you will be able to drive a vehicle in highly-automatic control in future?" not very confident/very confident.	3.25	1.16
TAM		
Perceived Usefulness (PU) (α = 0.89)		
PU1: I think driving a vehicle in highly-automatic control can make my driving easier	4.05	1.21
PU2: I think driving a vehicle in highly-automatic control can improve my driving safety performance	3.98	1.06
PU3: I think driving a vehicle in highly-automatic control can allow me to do other things in driving	4.18	1.14
PU4: Overall, driving a vehicle in highly-automatic control is useful for me	3.97	0.99
Perceived Ease of Use (PEU) (α = 0.80)		
PEU1: I think driving a vehicle in highly-automatic control is easy to learn.	3.84	1.01
PEU2: I think driving a vehicle in highly-automatic control is easy to control.	3.75	1.08
PEU3: I think driving a vehicle in highly-automatic control is easy to understand.	3.82	0.97
PEU4: Overall, I think driving a vehicle in highly-automatic control is easy to use.	3.91	1.10
Risk Probability in high-automatic driving (RiskAUTO) (α = 0.90)		
PROB_UR_AUTO: Probability assessment of accident in highly-automatic driving of a vehicle in urban road	3.10	1.11
PROB_RU_AUTO: Probability assessment of accident in highly-automatic driving of a vehicle in rural road	3.01	0.98
Worry in high-automatic driving (WorryAUTO) (α = 0.87)		
WORR_UR_AUTO: Worry in highly-automatic driving of a vehicle in urban road	3.58	1.13
WORR_RU_AUTO: Worry in highly-automatic driving of a vehicle in rural road	3.64	1.18
Risk Probability in manual driving (RiskMANUAL) (α = 0.81)		
PROB_UR_MANU: Probability assessment of accident in manually driving a vehicle in urban road	3.53	1.17
PROB_RU_MANU: Probability assessment of accident in manually driving a vehicle in rural road	3.62	1.05
Worry in manual driving (WorryMANUAL) (α = 0.78)		
WORR_UR_MANU: Worry in manually driving a vehicle in urban road	2.96	1.21
WORR_RU_MANU: Worry in manually driving a vehicle in rural road	2.98	1.17
Driving Habit (α = 0.85) Driving a car is something:		
H1: I do frequently.	3.67	0.75
H2: I do without having to consciously remember.	3.65	0.63
H3: I do without thinking.	3.73	0.83
H4: that belongs to my (daily, weekly, monthly) routine.	3.72	0.90
H5: I have been doing for a long time.	3.68	0.70
H6: I do automatically. [a]	3.71	0.89
H7: that makes me feel weird if I do not do it. [a]	3.62	0.75
H8: that would require effort not to do it. [a]	3.76	0.77
H9: I start doing before I realize I'm doing it. [a]	3.79	0.74
*H*10: I would find hard not to do. [a]	3.68	0.81
*H*11: I have no need to think about doing. [a]	3.70	0.84
H12: that's typically "me." [a]	3.72	0.68
Resistance to change		
Routine Seeking (RS) (α = 0.76)		
RS1: I generally consider changes to be a negative thing.	3.42	0.91
RS2: I'll take a routine day over a day full of unexpected events any time.	3.38	0.84
RS3: I like to do the same old things rather than try new and different ones.	3.40	0.79
RS4: Whenever my life forms a stable routine, I look for ways to change it. [b]	3.35	0.97
RS5: I'd rather be bored than surprised. [a]	3.51	0.86
Emotional Reaction (ER) (α = 0.79)		
ER1: If I were to be informed that there's going to be a significant change regarding the way things are done at work, I would probably feel stressed.	3.86	0.57
ER2: When I am informed of a change of plans, I tense up a bit.	3.82	0.75
ER3: When things don't go according to plans, it stresses me out.	3.90	0.86
ER4: If my boss changed the criteria for evaluating employees, it would probably make me feel uncomfortable even if I thought I'd do just as well without having to do any extra work. [a]	3.85	1.07
Short-Term Thinking (STT) (α = 0.82)		
STT1: Changing plans seems like a real hassle to me.	3.37	0.82
STT2: Often, I feel a bit uncomfortable even about changes that may potentially improve my life.	3.40	0.76
STT3: When someone pressures me to change something, I tend to resist it even if I think the change may ultimately benefit me.	3.36	0.94
STT4: I sometimes find myself avoiding changes that I know will be good for me.	3.42	0.83

(*continued on next page*)

Table 1 (*continued*)

Items	Mean	SD
STT5: Once I've made plans, I'm not likely to change them.[a]	3.41	1.12
Cognitive Rigidity (CR) (α = 0.75)		
CR1: I often change my mind. [b]	3.77	0.85
CR2: Once I've come to a conclusion, I'm not likely to change my mind.	3.79	0.70
CR3: I don't change my mind easily.	3.82	0.65
CR4: My views are very consistent over time.	3.73	0.75

[a] These items were ultimately eliminated due to the reliability-analysis and low factor loading.
[b] These items were reverse coded prior to running the analysis.

Table 2
Discrete choice model of the driving control.

Variable	Driving control	Estimate (*t*-test)
Constant	Manual control	–
	Partial-Automated control	0.45 (3.32)
	Highly-Automated control	2.68 (2.97)
Attitudes (ATT)	Manual control	−0.55 (-3.21)
	Partial-Automated control	–
	Highly-Automated control	0.91 (3.64)
Subjective Norm (SN)	Manual control	–
	Partial-Automated control	–
	Highly-Automated control	–
Perceived Behavioural Control (PBC)	Manual control	−0.24 (-2.62)
	Partial-Automated control	–
	Highly-Automated control	0.48 (3.04)
Perceived Usefulness (PU)	Manual control	–
	Partial-Automated control	0.31 (2.72)
	Highly-Automated control	0.94 (3.44)
Perceived Ease of Use (PEU)	Manual control	–
	Partial-Automated control	0.26 (2.40)
	Highly-Automated control	0.72 (2.51)
Risk Probability in high-automatic control	Manual control	–
	Partial-Automated control	–
	Highly-Automated control	–
Worry in high-automatic control	Manual control	0.60 (3.10)
	Partial-Automated control	–
	Highly-Automated control	−1.10 (-3.88)
Risk Probability in manual control	Manual control	–
	Partial-Automated control	–
	Highly-Automated control	–
Worry in manual control	Manual control	–
	Partial-Automated control	–
	Highly-Automated control	–
Driving Habit	Manual control	1.54 (3.20)
	Partial-Automated control	–
	Highly-Automated control	−0.48 (-2.90)
Routine Seeking	Manual control	0.77 (2.65)
	Partial-Automated control	–
	Highly-Automated control	−0.39 (-2.28)
Emotional Reaction	Manual control	–
	Partial-Automated control	–
	Highly-Automated control	–
Short-Term Thinking	Manual control	–
	Partial-Automated control	–
	Highly-Automated control	–
Cognitive Rigidity	Manual control	–
	Partial-Automated control	−0.21 (-3.11)
	Highly-Automated control	−0.56 (-2.80)
Number of observations	595	
Final log likelihood	−385.66	
Rho-square for the model	0.41	

Note1. Only statistically significant variables at CI 95% are retained in the final model.
Note2. T-statistics are shown in parentheses.

was considered as a function of the effects of latent variables (the model is described in Appendix A).

Table 3
The latent variable model part.

Attribute	Latent variable						
	ATT	SN	PBC	PU	PEU	RiskAUTO	WorryAUTO
AGE_1825	—	—	—	0.11 (2.96)	0.47 (4.32)	—	—
AGE_2639	—	—	—	—	—	—	0.34 (3.10)
AGE_4072	0.36 (2.98)	—		—	—	—	0.92 (3.88)
Male	—	—	−0.11 (-2.60)	−0.49 (-3.57)	—	—	−0.16 (-2.49)
WellEDU	0.75 (3.28)	—	—	—	—	—	—
FullTime	—	—	—	—	—	—	—
HHSIZE3+	—	—	—	—	—	—	—
CAR2+	—	—	—	0.53 (2.90)	0.64 (3.88)	—	—
INCOME	—	—	—	—	—	—	—
PEU	—	—	—	0.42 (3.17)	—	—	—
Random term	−0.27 (-7.84)	—	−0.83 (-12.93)	−0.70 (-6.73)	0.31 (8.13)	—	0.19 (4.22)
Attribute	Latent variable						
	RiskMANUAL	WorryMANUAL	Habit	RS	ER	STT	CR
AGE_1825	—	—	0.60 (4.22)	—	—	—	—
AGE_2639	—	—	0.92 (3.95)	—	—	—	—
AGE_4072	—	—	—	—	—	—	0.47 (5.32)
Male	—	—	0.41 (3.02)	0.30 (2.95)	—	—	0.17 (3.05)
WellEDU	—	—	—	—	—	—	—
FullTime	—	—	0.20 (2.60)	0.24 (3.68)	—	—	—
HHSIZE3+	—	—	—	—	—	—	—
CAR2+	—	—	0.78 (3.55)	—	—	—	—
INCOME	—	—	—	—	—	—	—
Random term	—	—	−0.53 (-12.65)	−0.40 (-5.38)	—	—	0.72 (4.68)

Note1. T-statistics are shown in parentheses.

5. Results

In this section, the estimation results of the hypothesised model (in Fig. 1) are presented. To test initial measurement and structural models, CFA and PCA were tested. The results of PCA and CFA are shown in Appendix B. For all constructs, internal consistency and scale reliability were satisfactory. All items were retained in their corresponding construct, except for seven and three items related to driving habit and resistance to change instruments, respectively (factor loading below 0.40). The CFA of the TPB scale showed satisfactory fit to the data ($\chi^2 = 68.32, df = 24, p < 0.01, RMSEA = 0.048, CFI = 0.91, TLI = 0.92$). Moreover, the CFA also showed a satisfactory fit for resistance to change scale ($\chi^2 = 234.56, df = 84, p < 0.01, RMSEA = 0.039, CFI = 0.92, TLI = 0.92$).

Table 2 shows the results of estimating the discrete choice model part. The dependent variable of choice includes three options of (1) manual control, (2) partial automated control, and (3) highly automated control. In the estimation process, a separate utility function was defined for each of the three options. As argued by Train (2003, p.24), if an analyst aims to estimate a choice model without a referent level of the dependent variable, at most $J - 1$ alternative-specific constants can be entered to the model, with one of the constants normalized to zero.

The final model has an acceptable goodness of fit (likelihood ratio index) of 0.41. The $t-test$ value statistic was used to determine the significance level of each of the model explanatory variables with a 95% Confidence Interval (CI). According to the model results, the variables reported in the main choice model at the level of five percent ($p-value < 0.05$) are significant (statistically different from zero). Another criterion for maintaining or eliminating an explanatory variable from the model was to have interpretive logic that follows the literature, which was controlled for variables. Table 3 shows the latent variable model part. In this model, the statistically significant correlation of demographic and socio-economic variables with psychological characteristics has been evaluated. Furthermore, the measurement model (the relationship between the latent variables and their indicators) is reported in Appendix C.

As shown in the discrete choice model (Table 2), eight variables including ATT, PBC, PU, PEU, WorryAUTO, Driving Habit, RS, and CR, were found to be statistically significant in different utility functions in a 95% CI. Other variables were not found to be statistically significant in the model.

In the latent variable model, some individual and socio-economic variables were found as correlated with latent psychological variables. For instance, well-educated individuals are positively associated with favourable attitudes towards driving a vehicle in highly-automated control.

Scenario and simulation methods were used to evaluate the effect of psychological variables estimated in the model on the share of change of each driving control. Since the psychological factors were on a 5-point Likert scale, the share of driving controls was calculated based on a one-unit increase of these factors (Mehdizadeh and Shariat-Mohaymany, 2020; Chorus and Kroesen, 2014; Mehdizadeh et al., 2019). Table 4 shows the share of options in the estimated model and different scenarios based on the psychological

Table 4
Predicting changes in the alternatives.

#	Scenario	Share of alternative (%)		
		Manual	Partial automation	High automation
0	Do Nothing*	15%	30%	55%
1	One-point increase in attitudes (ATT)	11%	30.5%	58.5%
2	One-point increase in Perceived Behavioural Control (PBC)	13.5%	30.5%	56%
3	One-point increase in Perceived Usefulness (PU)	12%	31%	57%
4	One-point increase in Perceived Ease of Use (PEU)	12.5%	31.5%	56%
5	One-point increase in Worry in highly-automated control	19.5%	31%	49.5%
6	One-point increase in Driving Habit	21.5%	28.5%	50%
7	One-point increase in Routine Seeking	18.5%	29.5%	52%
8	One-point increase in Cognitive Rigidity	18%	29%	53%

* The share of alternatives (market shares) is based on estimated HCM.

variables of the model. For instance, a unit of enhancement in people's attitudes toward using a highly automated control would result in a 3.5% increase in the share of the highly automated performance and a 4% decrease in the share of the manual control.

6. Analysis of results and discussion

According to the hypothetical model of the current study, most of the components of psychological theories are found to have a significant effect on different levels of automation. According to the developed model, people prefer highly automated control up to 55%, and partial automation up to 30%. Out of the various components, the habit of driving a conventional vehicle and the worry associated with driving a highly automated vehicle have the most positive effects on the utility of manual control. Also, a positive attitude towards the usefulness of the highly automated control had the most positive impact on the utility of highly automated control. The main contribution of our study to the literature is that we examined the relative roles of habits/resistance to change and beliefs in the choice of three driving controls. Our results go beyond previous findings, showing that driving habit with conventional cars has greater impact on drivers' preferences to choose a driving control compared to favourable beliefs about automated driving.

Regarding the relationship between the TPB and driving control (H_1), although the two components of attitudes and perceived behaviour control contributed significantly, the subjective norm did not play any significant role. Those who think highly automated control is beneficial and enjoyable most of the time are more likely to use highly automated control. This result ties in well with previous studies wherein favourable attitudes and perceived behaviour control could positively affect the use of highly automated vehicles (Bansal et al., 2016; Hohenberger et al., 2017; Nees, 2016; Schoettle and Sivak, 2014). Sensitivity analysis of the model shows that enhancing people's attitude towards using highly automated control can increase the share of highly automated control by 3.5% (from 55% to 58.5%) and can decrease the share of manual control by 4% (from 15% to 11%). Furthermore, people who are confident that highly automated control is easy for them are more likely to use highly automated control. Previous findings are inconsistent regarding the role of subjective norm on intention to use highly automated driving controls. While Buckley et al. (2018) found subjective norm to have a significant effect on intention to use autonomous driving, Nastjuk et al. (2020) did not find subjective norm to have a significant effect. We also found that the community, friends, and family do not put pressure on automatic car options. Perhaps a lack of attention to such technologies in the social media in the study area could account for the lack of significance of the link between social norms and intention to use automated driving controls.

The model of this study could reveal which segment of people had higher attitudes and PBC towards different levels of automation. Over 40-year-olds and well-educated people were more likely to have favourable attitudes toward highly automated control. Although some previous studies on AV acceptance have shown that older people are less receptive to AV compared to younger people (Payre et al., 2014; Kyriakidis et al., 2015), the present study showed that older people would be less interested in manual control than younger people. Further, women reported more behavioural control compared to men in highly automated control. Therefore, in addition to strengthening the attitudes and beliefs among such people, there should be campaigns to form a belief regarding the usefulness of automated controls among younger people (people under 40) and the male population.

In line with our hypothesis (H_2), the findings show that those who welcome the new technologies (better understand the ease of use and usefulness of technology) are more likely to prefer highly automated control most of the time when driving a vehicle. When comparing our results to those of older studies, it must be pointed out that such relationships have also been confirmed (e.g., Wu et al., 2019; Lee et al., 2019; Zhang et al., 2019; Panagiotopoulos and Dimitrakopoulos, 2018; Xu et al., 2018). One-unit enhancement in PU and PEU can increase the use of highly automated control by 2% and 1%, the partial automated control by 1% and 1.5%, and decrease the use of manual control by 3% and 2.5%. A similar pattern of results was obtained in Xu et al. (2018), showing that PU had a greater effect on intention to use AVs than PEU. Our findings suggest that enhancing the understanding of the usefulness of automated controls may lead to greater use of automatic options in vehicles. An in-depth analysis shows that the perception of the usefulness and ease of using a vehicle in highly automated controls has been reported to be stronger among the younger age group (18 to 25 years), women, and individuals with higher income. Thus, advertising campaigns could target other populations, such as people over the age of 25, men, and individuals with low income.

A further novel finding is that, driving control is a pre-planned (deliberate) process that can be strongly influenced by habit (H_3) as well. The analysis demonstrates that habit has a stronger effect on the formation of driving control than deliberate planning. People who routinely drive a conventional car and who are accustomed to this behaviour are more likely to prefer manual and partial automated control while driving a vehicle. This finding is partly confirmed by Gärling & Axhausen, (2003), Chen & Chao, (2011), Nordfjærn et al., (2014a), Şimşekoğlu et al., 2015 and Friedrichsmeier et al., (2013), demonstrating that people who have car use habit are less likely to switch to other mobility modes. Our study thus extends this concept showing habit as a significant predictor of intention to use different levels of driving controls. One-unit increase in a driving habit can reduce people's intention to use highly automated control by 5%. The driving habit is noticeable among younger people, men, full-time employees, and households who own two or more cars. Therefore, special policies should be adopted to target this group of citizens in the field of habit. For instance, special centres of automated vehicle can be built. People can experience automated driving once a day or weekly while using their conventional vehicles in their routine lives.

In line with the hypothesis of the current study (H_4), findings show that people who are resistant to change in their lives and cannot easily adapt their minds to new events and issues are less likely to use a vehicle in highly automated control and mostly prefer manual and partially automated control. We speculate that this might be due to the fact that such technologies (automated driving and vehicles) are not common in the study area, and most respondents are used to driving manually. In addition, they may distrust automated driving controls. One-unit increase in routine seeking and cognitive rigidity can reduce the use of highly automated control by 3% and 2%. In other words, people who avoid innovation in their lives and whose outlook is stable over time are less likely to use highly automated controls. Men, full-time workers, and people older than 40 were significantly more resistant to change. It seems that the sudden change of manual (conventional) cars to highly automatic ones may have a negligible effect on the behaviour of these people, and it would be better for policymakers to act with caution in the technological transition to automated driving. Implementing programs, such as driving simulators and free driving tests with automated vehicles may lead to positive changes in people's behaviour in adapting to the use of highly automated control while driving a vehicle.

Interestingly, among the various components of risk perception and worry, the worry component in the case of driving in highly automated control was associated with a reduced likelihood of intention to use highly automated control. This implies the significance of some citizens' concerns and worries regarding the safety and security of driving in highly automated controls. Although the assessment of the possibility of an accident in automatic and manual performance was not found to have a significant effect, the worry was found to be very important in choosing the driving control. To the best of our knowledge, this study is among the first which finds worry as a statistically significant predictor of intention to use different driving controls. However, this finding is consistent with prior research in other fields (e.g., Moen and Rundmo, 2006; Oltedal and Rundmo, 2007). This finding partly supports our hypothesis (H_5). Increase in worry by one degree can decrease the use of highly automated control by 5.5% and increase the use of manual control by 4.5%. This suggests that policymakers, in addition to addressing the objective security and safety issues, should address the subjective safety and security issues of vehicle users. The analysis shows that worry is felt significantly more among respondents older than 26 years and women. Therefore, reducing the worry of this population regarding automated versions of vehicles can increase the integrated use of highly automated vehicles.

7. Summary and conclusion

In this study, the role of psychological factors on different levels of driving controls was investigated. The findings showed that the habit of driving with conventional cars and the feeling of worry when using highly automated control has a significant role in how a vehicle is driven. In addition to the role of habit and comfort with life routine, some people also believe in the usefulness of highly automated control, which directly increases the likelihood of using highly automated controls. This study leads to a better understanding of the factors affecting the driving control of people with a vehicle. Based on findings, the following policies and practices are proposed.

Breaking the habit of driving conventionally and making people more flexible to changing their driving control should be one of the first steps of policymakers. Policies such as providing free driving tests with highly automated vehicles for citizens may neutralize the role of driving habits and resistance to change regarding new technology. Policymakers could work with operators and manufacturers to facilitate specific test areas outside real-traffic zones. As studies have shown, many drivers are uncomfortable when switching to automated control for the first time (Nunez, 2017; Nastjuk et al., 2020), these test areas can alleviate concerns about traffic risks and trust barriers. Test drives and pilot studies should focus on those with greater levels of innovation. Since these people with a high level of innovation are more likely to adopt automated controls (Nastjuk et al., 2020).

Campaigns should be launched to strengthen attitudes and beliefs regarding the usefulness of highly automated vehicles and their automatic options among younger people (people under 40) and the male population. Additionally, policymakers should do more to activate and raise public awareness about technology and highly automated vehicles. Providing transparent and strong security standards for highly automated vehicles could help to reduce concerns about automated controls.

The campaigns should explain the benefits of using automatic controls between different groups, such as people over 25, men, and people with lower incomes, and address people's worry regarding the highly automatic control of vehicles.

The present study is not without limitations, and most of these limitations are due to their nature and subject matter. First of all, since highly automated vehicles are uncommon in the study area, respondents may not be familiar with how to control them, and their responses are based on our descriptions/their information on the various driving options. During the survey, however, efforts were made to provide an explanation of different levels of automation that was accurate and honest. However, stated preferences in a hypothetical imagined situation are not the same as actual preferences, as individuals often consider the actions or strategies of other individuals when stating preferences. Furthermore, participants may have only limited cognitive resources, which limits their ability to mentally reconstruct a realistic environment (Brandts and Charness, 2000; Jones et al., 2011). To reduce the probability of making cited errors, survey assistants described the main features of different driving controls (levels) of automation from Level 0 to Level 4 both orally (through a simple language) and schematically (via a picture depicting different levels of automation) (Ludwig, 2007). Simulations or laboratory studies, as well as providing driving experience, and testing different automated options, can lead to a more accurate view for people on how to choose their driving control. Additionally, everyone in this study used a car, so people who have never driven a car might operate the automated vehicle differently than those who have. Moreover, the present study was conducted in the Middle East, where people are not as familiar with highly automated features as people in developed countries, which may lead to different results in other communities. The results of this study should therefore be carefully analysed and applied to other communities.

CRediT authorship contribution statement

Hossein Karami: Conceptualization, Writing – original draft, Methodology, Software. **Ali Karami:** Data curation, Writing – original draft, Visualization, Investigation. **Milad Mehdizadeh:** Writing – review & editing, Supervision, Methodology, Formal analysis, Validation.

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

The utility function of the options can be written in the form of Eq. (1):

$$U_{xy} = CON_y + \lambda_{yz} LAT_{xz} + \varepsilon_{xy} \tag{1}$$

where,.

U_{xy}: the utility that individual × is associated with the driving control y.
CON_y: the vector of constants specific for y −1 driving control group.
LAT_{xz}: zth latent variable (λ_{yz} is the respective coefficient).
ε_{xy}: error term that is assumed to be identically and independently distributed (IID) extreme value type 1.

Eq. (2) indicates how the latent variable (LAT) itself can be expressed:

$$LAT_{xz} = \alpha_z DSE_{xz} + \sum_{s \neq z} \tau_s LAT_{xs} + \omega_{xz} \forall s, z \in Z \tag{2}$$

where,.

DSE_{xz}: is a vector of demographic and socioeconomic variables predicting z^{th} latent variable.
τ_s: is a coefficient of latent variable s that hierarchically associates with latent variable z.
ω_{xz}: is a normal distributed error term with zero mean and standard deviationσ_{wz}, capturing the random element of the latent variable.

In the measurement equation, the indicator of latent variables (LAT_{xz}) is identified by Eq. (3):

$$I_{xfz} = \gamma_{fz} + \zeta_z LAT_{xz} + \upsilon_{xfz}, f = 1, \ldots, F \tag{3}$$

where,.

I_{xfz}: is the f th indicator for z th latent variable of individual$x$.
γ_{fz}: is the constant in the measurement equations for indicator f of the latent variable$z$.
ζ_z: is the coefficient associated with the latent variable$z$.
υ_{xfz}: shows a normally distributed error term with zero mean and standard deviationσ_{wz}.
γ andζ: are normalised to zero and one for the first indicator of each latent variable for identification purposes.

Regarding the theory of the random utility maximization, based on Eq. (4) a driving control is chosen for person x in discrete choice part:

$$y_{hx} = \left\{ \begin{matrix} 1, & if & U_h = Max_y(U_{yx}) \\ 0, & otherwise & \end{matrix} \right\} \tag{4}$$

where,

y_{hx}: is the choice indicator, taking the value 1 if group h is chosen (h has the highest utility among all driving controls in the choice set) and takes the value of 0, otherwise.

As for the distributions of the latent variable and the indicator, the following equations are used:

$$f_{LAT}(LAT_{xz}|DSE_{xz};\alpha_z,\tau_s,\sigma_{wz}) = \frac{1}{\sigma_{wz}}\varphi\left(\frac{LAT_{xz} - \left(\alpha_z DSE_{xz} + \sum_{s\neq z}\tau_s LAT_{xs}\right)}{\sigma_{wx}}\right) \tag{5}$$

$$f_I\left(I_{xz}|LAT_{xz};\gamma_z,\zeta_z,\sigma_{vz}\right) = \frac{1}{\sigma_{vfz}}\varphi\left(\frac{I_{xz} - \left(\gamma_{fz} + \zeta_z LAT_{xz}\right)}{\sigma_{vz}}\right) \tag{6}$$

where,.

φ: is the standard normal distribution function.

Meanwhile, the choice probability can be specified by Eq. (7):

$$P_{xy} = \int_{\omega} P_{xyz}(LAT_{xz}(\omega_{xz}))f_{LAT}(\omega_{xz})f_I(LAT_{xz}(\omega_{xz}))f(\omega)d\omega \tag{7}$$

A full information approach using PythonBiogeme (Bierlaire, 2016) is used for estimation purposes.

Appendix B

Tables B1 and B2.

Table B1
The results of PCA.

Constructs	Items (factor loading)
Perceived Usefulness (PU) (α = 0.89)	PU1 (0.88), PU2 (0.84), PU3 (0.80), PU4 (0.83)
Perceived Ease of Use (PEU) (α = 0.80)	PEU1 (0.91), PEU2 (0.83), PEU3 (0.78), PEU4 (0.77)
Risk Probability in high-automatic driving (RiskAUTO) (α = 0.90)	PROB_UR_AUTO (0.86), PROB_RU_AUTO (0.79)
Worry in high-automatic driving (WorryAUTO) (α = 0.87)	WORR_UR_AUTO (0.76), WORR_RU_AUTO (0.81)
Risk Probability in manual driving (RiskMANUAL) (α = 0.81)	PROB_UR_MANU (0.85), PROB_RU_MANU (0.79)
Worry in manual driving (WorryMANUAL) (α = 0.78)	WORR_UR_MANU (0.76), WORR_RU_MANU (0.78)
Driving Habit (α = 0.85)	H1 (0.72), H2 (0.70), H3 (0.70), H4 (0.66), H5 (0.63)

Table B2
The results of CFA.

Scale	Constructs	Item (standardised coefficient in p < *0.001*)	Summary of fit statistics
TPB	Attitudes (ATT) (α = 0.86)	ATT1 (0.83), ATT1 (0.76), ATT1 (0.81), ATT1 (0.74)	
	Subjective Norm (SN) (α = 0.84)	SN1 (0.73), SN1 (0.70), SN1 (0.65)	χ^2 = *68.32, df* = *24, p* < *0.01, RMSEA* = *0.048, CFI* = *0.91, TLI* = *0.92*
	Perceived Behavioural Control (PBC) (α = 0.79)	PBC1 (0.84), PBC1 (0.81)	
Resistance to change	Routine Seeking (RS) (α = 0.76)	RS1 (0.80), RS1 (0.76), RS1 (0.75), RS1 (0.68)	
	Emotional Reaction (ER) (α = 0.79)	ER1 (0.76), ER1 (0.77), ER1 (0.70)	
	Short-Term Thinking (STT) (α = 0.82)	STT1 (0.84), STT1 (0.82), STT1 (0.78), STT1 (0.73)	χ^2 = *234.56, df* = *84, p* < *0.01, RMSEA* = *0.039, CFI* = *0.92, TLI* = *0.92*
	Cognitive Rigidity (CR) (α = 0.75)	CR1 (0.75), CR1 (0.71), CR1 (0.68), CR1 (0.63)	

Appendix C

See Table C1.

Table C1
The measurement relationship in the latent variable model part.

Latent factors	Indicator	γ		ζ		σ	
		Estimate	*t*-test	Estimate	*t*-test	Estimate	*t*-test
ATT	$I_{2\text{-TRUST}}$	0.78	4.69	1.43	15.04	−0.17	−5.11
	$I_{3\text{-TRUST}}$	0.50	9.14	1.23	17.29	−0.46	−10.65
	$I_{4\text{-TRUST}}$	0.24	3.67	1.64	12.75	−0.23	−13.48
PBC	$I_{2\text{-PBC}}$	0.57	8.32	1.87	12.15	0.16	5.76
PU	$I_{2\text{-PU}}$	−0.34	−4.06	1.13	25.43	−0.61	−8.59
	$I_{3\text{-PU}}$	−0.27	−2.79	1.45	20.68	−0.44	−9.29
	$I_{4\text{-PU}}$	−0.68	−7.72	1.36	16.42	−0.82	−5.32
PEU	$I_{2\text{-PEU}}$	−0.94	−5.24	1.76	10.35	−0.84	−7.16
	$I_{3\text{-PEU}}$	−0.65	−3.82	1.63	18.21	−0.19	−5.90
	$I_{4\text{-PEU}}$	−0.37	−8.32	1.61	7.57	−0.63	−12.47
WorryAUTO	$I_{2\text{-WorryAUTO}}$	−0.39	−7.02	2.15	24.74	−0.73	−14.46
Habit	$I_{2\text{-Habit}}$	0.23	6.12	1.13	14.68	−0.48	−5.80
	$I_{3\text{-Habit}}$	0.38	8.28	1.18	15.23	−0.57	−11.10
	$I_{4\text{-Habit}}$	0.52	4.71	1.03	15.29	−0.48	−9.85
	$I_{5\text{-Habit}}$	0.41	3.11	1.38	12.55	−0.93	−6.69
RS	$I_{2\text{-RS}}$	−0.83	−3.77	1.03	6.39	−0.73	−14.23
	$I_{3\text{-RS}}$	−0.56	−5.82	1.14	14.74	−0.19	−8.86
	$I_{4\text{-RS}}$	−0.98	−4.15	1.08	11.44	−0.63	−13.52
CR	$I_{2\text{-CR}}$	0.49	8.36	1.84	18.73	−0.16	−15.88
	$I_{3\text{-CR}}$	0.63	7.94	1.76	14.90	−0.32	−9.28
	$I_{4\text{-CR}}$	0.33	11.23	1.93	23.27	−0.52	−12.98

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