The well-being of Autonomous Vehicles (AVs) users under uncertain situations

Autonomous vehicles (AVs) have made significant progress towards large-scale deployment, offering numerous advantages to society. These benefits include enhanced comfort, safety, efficient utilization of resources (such as energy and land), and environmental protection. Moreover, the potential positive impact of AVs on people's health, such as reducing stress during traffic, is often emphasised. Research suggests that reducing driver responsibilities and allowing leisure activities like reading or entertainment can contribute to overall well-being. However, these assumptions are primarily based on theoretical grounds. This paper aims to investigate the correlation between the level of automation in AVs and public well-being responses, particularly in uncertain and challenging driving scenarios. Through four comprehensive studies, we discovered a significant decrease in well-being responses as the level of automation increases in vehicles. Nonetheless, this pattern is subject to sensitivity based on the level of uncertainty present in the driving scenarios. Consequently, when individuals face higher uncertainty, they tend to experience greater calmness and relaxation at higher levels of automation compared to lower levels. These findings offer valuable insights into comprehending the psychological barriers that influence public perception of AVs.

CCS CONCEPTS • Autonomous Vehicles • Well-being • Experimental Research • Consumer research

1 INTRODUCTION

Autonomous Vehicles (AVs) are spearheading a transformative revolution in the transportation industry. With human error accounting for 95% of accidents, the paramount and highly sought-after advantage of AVs is improved road safety [2]. Currently, the AV industry is developing vehicles with varying degrees of autonomy [1]. To establish a standard framework, manufacturers and regulators adhere to the level of autonomy classification outlined by the Society of Automotive Engineers (SAE) [3]. This classification system encompasses six levels of automation, ranging from Level 0 to Level 5. At Level 0, the human driver maintains full control of the vehicle, with no autonomous capabilities present. Level 1 entails single-driver assistance features that aid the human driver in steering, acceleration, or deceleration, while still requiring the driver to assume responsibility for operating and controlling the vehicle at all times. Level 2 introduces increased autonomy, where AVs can control both steering and acceleration/deceleration, but the driver must remain actively engaged and supervise the vehicle continuously. Moving further up the autonomy scale, Level 3 AVs possess enhanced automation capabilities, allowing them to respond to changes in the driving environment. However, drivers at Level 3 must remain alert, ready to take control of the vehicle and supervise the driving journey. Level 4 represents a significant advancement, as AVs can independently navigate entire journeys on highways and in city traffic. Although Level 4 AVs do not necessitate human interaction, human drivers can regain control of the vehicle under specific conditions, such as severe weather. Lastly, Level 5 signifies full automation, where humans relinquish control entirely, and these vehicles lack a steering wheel. According to the European Road Transport Research Advisory Council [4], all levels of AVs will be commercially available in the EU market by 2030.

Although Autonomous Vehicles (AVs) are poised to be the future of car manufacturing, consumer adoption of this technology still faces significant resistance [5]. Many individuals remain hesitant to relinquish critical decision-making, whether partially or entirely, to AI and machines. Concerns surrounding AVs revolve around the fear of losing control [6], a perceived loss of freedom [7], distrust in technology [6], and concerns regarding perceived risks [8]. These public apprehensions about AVs can become even more pronounced during uncertain and critical situations, such as delegating the driving task to AVs under challenging weather conditions. Consumer behavior research indicates that when adopting new technology, individuals seek well-being, happiness, and positive emotions [9]. Furthermore, the perception of well-being significantly influences consumer decision-making when considering the purchase of a technological product [10]. Given the inherent uncertainty associated with AVs, understanding consumers' perception of well-being towards this new technology becomes crucial for comprehending future consumer behavior. While there is existing research that addresses public opinions on acceptance, trust, and ethical implications of AVs [6,7,8], the area of health and well-being perception has received relatively less attention, as highlighted in a recent review [11]. Therefore, there is a need for further investigation into how AVs impact individuals' well-being and how these perceptions shape consumer behavior in the future. Expanding our understanding of the interplay between AVs and well-being perception will provide valuable insights for the development and adoption of this technology.

This paper's objective is to examine the variations in well-being responses among individuals across different levels of AV automation and explore the underlying reasons for these differences. The practical significance of this study lies in the valuable insights it provides regarding public responses to varying AV levels, particularly in uncertain scenarios. This knowledge can inform effective approaches when engaging with the public and policymakers. Additionally, the study contributes to the theoretical understanding of the psychological mechanisms that drive individuals' well-being responses in uncertain scenarios when utilising different levels of AV automation.

2 LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

In this section, we begin by examining the similarities and differences in people's well-being responses to the travel experience. We present our first hypothesis, which suggests that individuals experience greater levels of well-being as the level of automation increases in autonomous vehicles (AVs). Additionally, we propose that the perceived uncertainty during the travel journey can act as a moderating factor in the relationship between well-being and the level of automation.

2.1 People’s well-being and travel experience

Well-being is a fundamental concept that encompasses an individual's state of comfort, health, and happiness [12]. It reflects the overall quality of life in various dimensions, including physical, material, social, and emotional well-being [13]. The travel experience is closely associated with numerous health and well-being outcomes, and in recent years, scholars and industry professionals have increasingly focused on exploring this connection [14]. When considering well-being in the context of travel experience, it refers to the emotions individuals experience during their trips and how they evaluate them. The choices made when selecting a mode of transportation significantly influence how people perceive their travel [15]. Specifically, private travel is often associated with the highest levels of travel satisfaction, while public transit, particularly buses, tends to receive fewer positive evaluations. Furthermore, many studies indicate a negative impact of trip duration on travel satisfaction, as longer trips can pose mental and physical burdens [15, 16].

The potential benefits of autonomous vehicles (AVs) on well-being, particularly in reducing negative emotions during traffic navigation, have been widely discussed. Researchers have argued that by reducing the responsibilities of drivers and allowing them to engage in activities like reading or entertainment (only at Level 3 and above), AVs can have a positive impact on well-being [17]. However, these arguments are largely theoretical, as empirical studies examining the effects of increasing the level of automation on well-being and travel experience are still lacking in the literature. In this study, we make the assumption that increasing the level of automation in AVs would have a positive influence on people's well-being. Based on this assumption, we propose the following hypothesis.

H1 Increasing the level of automation would introduce a higher level of well-being during the travel journey.

2.2 Uncertainty in AVs

As mentioned in the introduction, public concerns regarding autonomous vehicles (AVs) may potentially escalate in uncertain and unfamiliar circumstances, such as relying on AVs to drive under challenging weather conditions. Studies have demonstrated that higher levels of uncertainty are linked to various responses, including acceptance, trust [18], moral judgments [19], and assigning blame to automation [20]. Perceived uncertainty has also been found to contribute to delayed judgment and may necessitate an adaptive approach to decision-making [21]. Johnson [22] argues that perceived uncertainty, particularly in situations where probabilities are difficult to identify, should receive greater attention in consumer research. They propose that the provision of information does not necessarily guarantee a reduction in uncertainty. In fact, the process of gathering information about a decision may even amplify uncertainty by revealing previously unrecognized areas of ignorance.

While perceived uncertainty and its impact on public acceptance, trust, and well-being have been explored in the literature on autonomous vehicles (AVs), there has been a lack of attention given to the different types of uncertainty (e.g., [23]). Researchers have primarily examined uncertainty conditions as a singular component. Milliken [24] suggests that perceived uncertainty encompasses various types that individuals encounter when trying to understand and respond to changes in their environment. These types include effect uncertainty, response uncertainty, and state uncertainty. Effect uncertainty refers to the inability to predict the impact of a future state of the environment on decision-making. In this scenario, the predictor is familiar with the future state of the environment but cannot determine the effect it will have on the current decision. Response uncertainty, on the other hand, involves a lack of knowledge regarding response options and/or the inability to predict the likely consequences of a particular response choice. State uncertainty, as defined by Milliken, is characterized by an inability to predict how the environment will impact the predictor's decision. Unlike effect uncertainty, the predictor lacks knowledge about the future state of the environment in state uncertainty. Evidence suggests that failure to differentiate among these types of uncertainty can lead to confusion and incorrect assumptions [24].

In a related study, Franklin et al. [24] examined how the public attributes blame to machines in uncertain situations. However, their research primarily focused on investigating different levels of perceived uncertainty. They explored three levels of uncertainty: (a) simple driving situations that are easy to navigate without making mistakes, (b) complex driving situations with added difficulty that require a certain level of competence to navigate without errors, and (c) novel situations that involve unique circumstances requiring novel inferences and may not have been part of pre-training.

In this paper, we highlight the importance of considering uncertainty types and levels when examining the role of uncertainty on public well-being while using autonomous vehicles (AVs). By addressing these factors, future research can propose mechanisms to mitigate the negative impact of uncertainty-related concerns and design AVs that promote better well-being. Based on this rationale, we propose the following hypothesis:

H2: Higher levels of effect uncertainty associated with higher levels of automation result in positive well-being responses.

H3: Higher levels of response uncertainty associated with higher levels of automation result in positive well-being responses.

H4: Higher levels of state uncertainty associated with higher levels of automation result in positive well-being responses.

3 CONCEPTUAL MODEL AND RESEARCH TOOLS

The primary aim of this study is to investigate the intricate relationship between the level of automation, perceived uncertainty, and well-being. While there has been significant research conducted on this topic, the precise connection between these constructs remains unclear. In the following sections, we present our research model, which emphasizes the multidimensional nature of well-being, perceived uncertainty, and the level of automation. Furthermore, we illustrate the relationships between these constructs, providing insights into their interplay.

3.1 Aims and conceptual model

Building upon the literature review presented earlier, this paper seeks to investigate the relationship between the level of automation, well-being, and perceived uncertainty. Specifically, this study examines how the level of automation in autonomous vehicles (AVs) can influence individuals' perceptions of well-being in uncertain situations. The primary focus is on understanding how drivers' well-being is affected by different levels of automation when faced with uncertain circumstances, taking into account various types of uncertainty. Our conceptual model, depicted in Figure 1, illustrates the framework for this investigation.

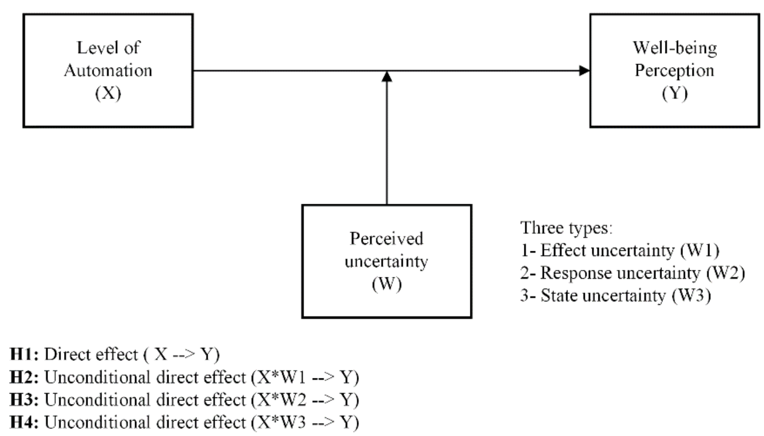

Figure 1: shows the hypothetical model with which to describe the relationships among the level of automation (X), perceived uncertainty related to one uncertainty type (Effect W1, Response W2, State W3), and Well-being perception (Y). We examine the significance of one direct effect (X → Y) and three indirect effects: indirect effect 1 (X→W1→Y); indirect effect 2 (X→W2→Y); indirect effect 3 (X→W3→Y); which correspond to H1, H2, H3, H4, respectively.

3.2 Measures and tools

Car vignettes and perceived uncertainty scenarios

To describe all different levels of AVs, we created three car vignettes. Our approach involved simplifying the space of AV levels of automation compared to the 6-level SAE classification. This simplification was done to clearly convey the drivers' roles in controlling the AV to our participants. The reason for adopting this simplified space was to ensure the driver's role was easily understood. Additionally, existing literature provides clear evidence that the public still experiences confusion regarding the distinctions within the 6-level SAE classification [25]. Our simplified space includes three distinct driver roles: Driver in charge (Level 1 and Level 2), Driver as the supervisor (Level 3 and Level 4), and Driver not in charge (Level 5). Throughout all the experiments, we assigned a unique name to each car vignette to foster a sense of attachment to the described vehicle. The car names used were 'You are in charge' car, 'You are the supervisor' car, and 'You are not in charge' car.

Then, we developed nine scenarios to capture perceived uncertainty, encompassing three types of uncertainty each combined with three levels of uncertainty. These scenarios were designed to create uncertain driving situations. To construct the scenarios, we followed Milliken's [24] definition of perceived uncertainty types and utilized Franklin et al.'s [20] categorization to determine uncertainty levels. While the scenarios we used were hypothetical, they were realistic and anticipated to occur in the future. In a separate experiment, we conducted validation tests for both the car vignettes and uncertainty scenarios. A concise description of all the car vignettes and uncertainty scenarios can be found in Table 1.

Table 1: Brief description of car vignettes and uncertainty scenarios used in our experiments.

Car Vignettes	**Brief description**
'You are in Charge' car	The driver is responsible for the car all the time and the car has only driver assistance that allows for maintaining a steady speed in certain situations.
'You are the supervisor' car	The driver is responsible to take control when needed and the car can drive itself in most situations except severe and difficult situations.
'You are not in Charge' car	The driver has no control over the car and cannot take control at any time.
Uncertainty Scenario	**Brief description**
Low response uncertainty	The car is facing a temporary STOP which is a clearly visible sign.
Medium response uncertainty	The car is facing a temporary STOP which is a partially visible sign.
High response uncertainty	The car is facing a temporary STOP hardly visible sign.
Low effect uncertainty	The car is driving under green weather advice, i.e., the weather is nice and clear.
Medium effect uncertainty	The car is driving under yellow weather advice, i.e., the weather is challenging and there are some disruptions anticipated on the route of travel.
High effect uncertainty	The car is driving under an amber warning, i.e., the weather is challenging and there is a high likelihood that there will be significant disruptions on the route of travel.
Low state uncertainty	A rental car is driving around the local neighbourhood.
Medium state uncertainty	A rental car is driving in a city in the UK that the driver visits for the first time.
High state uncertainty	A rental car is driving in a country that the driver visits for the first time.

Well-being and Sociodemographic

We used WHO-5 Well-being Index to measure participants' well-being during our experiments [26]. The scale measures well-being with five self-rating items with a higher score indicating higher well-being. Because the scale measures health-related quality of life, not all the items are valid to be used in our experiment. We, therefore, chose the first two items in the questionnaire: "*I will feel cheerful in good spirits when using X car in this situation*" and "*I will feel calm and relaxed when using X car in this situation*", with X referring to the cars' names. These questions were made on a 7-Likert scale. Participants were also asked to provide eight sociodemographic factors - age, gender, annual income, ethnicity, marital status, qualifications, children, and disability. Participants were also asked to provide five driving experience factors – driving license, last car purchase type (second-hand or new), driving style, years of driving, and involvement in a previous car accident.

3.3 Manipulation checks

We first conducted three experiments to check the validity of our instruments. Our aim is to ensure that participants can recognise a distinct level of automation in each car vignette ("*You are in charge*" car, "*You are the supervisor*" car, "*You are not in charge*" car). The goal also is to check whether each uncertainty scenario is representative of a distinct type (Effect, Response and state) and level (low, medium and high). All participants completed all three experiments with an approximate time of 4-5 minutes to complete each experiment.

Each experiment included three car vignettes and three scenarios of one uncertainty type, in a (3x3) between-subject experiment. That means experiments varied in their type of perceived uncertainty scenarios (effect, response and state). The uncertainty scenarios presented in each experiment varied in their level of uncertainty (low, medium and high). In each experiment, participants read one car vignette ('*You are in charge*' car, '*You are the supervisor*' car, and '*You are not in charge*' car) and rated their perceived level of automation ranging from '*Extremely low automation*' to '*Extremely high automation*' on a 7-Likert scale. Then, participants were introduced to one uncertainty scenario (low, medium or high) and completed a perceived uncertainty scale adopted [27]. Participants who were involved in the validity-check experiments were not involved in the main experiments.

3.3.1 Results

Car vignettes

In all three experiments, one-way ANOVA tests were conducted to compare the impact of car vignettes on participants' perceived level of automation. The results of the one-way ANOVA revealed a statistically significant difference in the perceived level of automation between at least two car vignettes across all three experiments [Experiment 1: $F(2, 299) = 471.077$, $p << 0.01$; Experiment 2: $F(2, 299) = 396.734$, $p << 0.01$; Experiment 3: $F(2, 299) = 379.264$, $p << 0.01$]. Subsequently, Tukey's HSD test was conducted for multiple comparisons, which indicated that the mean values of the perceived level of automation were significantly different across all pairs of groups. For detailed information regarding participants' perceived level of automation, please refer to Table 2, which includes descriptive statistics.

Table 2: Descriptive statistics of perceived level of automation across three pre-experiments.

Car Vignettes	**Experiment 1**		**Experiment 2**		**Experiment 3**	
	N	**Mean**	**N**	**Mean**	**N**	**Mean**
'You are in charge' car	102	2.10 (1.349)	**100**	2.26(1.418)	**101**	2.10(1.207)
'*You are the supervisor*' car	99	4.35 (1.264)	**101**	4.54(1.196)	**101**	4.65(1.062)
'*You are not in charge*' car	101	6.87 (.503)	**101**	6.79(.682)	**100**	6.56(1.174)

Uncertainty types and levels

For each experiment, we used multiple linear regression to test if car vignettes and uncertainty scenarios can significantly predict the type and levels of uncertainty. In the first experiment, we presented effect uncertainty scenarios with three levels of uncertainty (low, medium and high). The overall regression was statistically significant ($R2 = 0.235$, $F(2,299) = 45.917$, $p<<0.01$). It was found that car vignettes significantly predicted the perceived effect uncertainty of our participants ($\beta = 0.436$, $p <<0.01$]). That means participants' effect uncertainty was increased when the car level of automation increased. It was also found that effect uncertainty scenarios significantly predicted effect uncertainty ($\beta = 0.217$, $p <<0.01$). That means the perceived uncertainty of our participants significantly increased when the level of effect uncertainty increased in our scenarios (See Table 3).

Experiment 2 was to test response uncertainty scenarios. Then, multiple linear regression was used to test if car vignettes and response uncertainty scenarios can significantly predict the perceived response uncertainty of our participants. The overall regression was statistically significant (R2 = 0.315, F (2,299) = 68.845, p<<0.01). It was found that car vignettes significantly predicted the perceived effect uncertainty of our participants (β = 0.540, p <<0.01]). That means participants' response uncertainty was increased when the care level of automation increased. It was also found that effect uncertainty scenarios significantly predicted effect uncertainty (β = 0.150, p <<0.02). That means the response perceived uncertainty of our participants significantly increased when the level of response uncertainty increased in our scenarios (See Table 3).

Finally, state uncertainty scenarios were tested in experiment 3. The overall regression was statistically significant (R2 = 0.069, F (2,299) = 11.307, p<<0.01). It was found that car vignettes significantly predicted the perceived state uncertainty of our participants (β = 0.496, p <<0.01). That means participants state uncertainty was increased when the care level of automation increased. It was found that state uncertainty scenarios significantly predicted perceived state uncertainty (β = 0.242, p <<0.01). That means the perceived uncertainty of our participants significantly increased when the level of state uncertainty increased in our scenarios.

Table 3. Regression coefficients for predicting the perceived certainty of participants.

	Variable	B	95% CI	β	t	p
Effect	**Car vignettes**	.813	[.999,.627]	.436	-8.609	0.000
	Effect uncertainty scenarios	.406	[.591,.220]	.217	-4.294	0.000
Response	**Car vignettes**	1.198	[1.407,.989]	.540	-11.291	0.000
	Response uncertainty scenarios	.333	[.542,.124]	.150	-3.138	0.002
State	**Car vignettes**	1.322	[1.575, 1.069]	.496	-10.289	0.000
	State uncertainty scenarios	.646	[.899, .392]	.242	-5.014	0.000

3.4 Experimental design

To answer our research question, we designed four studies. Ethical approval was obtained from University of Southampton ethics committee. The study protocol considered all ethical considerations of the study, starting from asking participants to read the information sheet to inform them about the withdrawal process at any time during the study. Participants were allocated randomly across all the study conditions to eliminate systematic selection bias. The sample size of each experiment was chosen to ensure the inclusion of at least 100 participants for each condition.

3.4.1 Study 1 – Direct relationship between the level of automation and well-being

Participants

We collected data from 329 participants (United Kingdom residents) recruited from Prolific platform. We excluded four participants who did not complete the experiment, leaving us with 325. Our sample included participants with the age range 18-80 (median: 43), 45.9% were males, 63% had annual income ranging between 10K-50K and 48% were driving cars every day.

Experiment procedure

Participants were shown three car vignettes in random order. Each experimental condition represented a car description of a distinct level of automation ('*You are in charge*' car, '*You are the supervisor*' car, and '*You are not in charge*' car) in a 3-level within-subjects design. In each condition, participants first read a description of the car and then were asked to complete WHO-5 Well-being Index (on a 7-Likert scale).

3.4.2 Study 2 – Indirect relationship between the level of automation and well-being responses (uncertainty as a moderator)

Study 2 was divided into three main studies (Study 2.A, Study 2.B and Study 2.C). Each study examines the role of one type of uncertainty (Effect, Response and State) as a moderator between the level of automation and well-being.

Participants

In Study 2.A, we collected data from 302 participants (UK residents) recruited from Prolific platform. We excluded one participant who did not complete the experiment, leaving us with 301 participants. Our sample included participants in the age range 18-74 (median: 28), 34.9% were males, 57.2% had annual income ranging between 10K-50K, and 50.5% were driving cars every day.

Then, Study 2.B included data gathered from 341 participants (UK residents) who were recruited through the Prolific platform. No participants were turned away from this study. Participants in our sample ranged in age from 18 to 86 (median: 32); 50.1% of them were men; 65.7% had annual incomes between 10K and 50K, and 52.2% drove cars daily.

Finally, we collected data from 351 participants (UK residents) in Study 2.C who were recruited through the Prolific platform. We did not exclude any participants from this study. The ages of participants in our sample ranged from 18 to 77 (median: 36); 50% were men; 65% had yearly salaries between 10K and 50K, and 49.9% drove a car on a regular basis.

Experimental procedure

Across three studies, participants were randomly allocated to three out of nine conditions following a mixed design – a within-subject factor followed by a between-subject factor. Each participant was presented with three car descriptions in a random order (Within-Subjects factor). Then, each car description was followed by a randomly selected uncertainty scenario - Low, Medium, or High – (Between-Subjects factor). We included scenarios of effect uncertainty only in Study 2.A, scenarios of response uncertainty in Study 2.B and scenarios of state uncertainty in Study 2.C. After each scenario, participants were asked to complete well-being WHO5 index. At the end of each experiment, participants provided basic demographic information (e.g., age, gender, income, education) and basic driving experience (e.g., how regularly do they drive?).

4 RESULTS

Study 1

The estimated marginal means (EMMs) of well-being across Study 1 conditions are illustrated in Figure 2. Analysis of the Covariance (ANCOVA) test was conducted with well-being as the dependent variable; Car type as the independent variable; and gender, age, ethnicity, marital status, education level, children, disability, driver's license holder, accident involvement, and driving style as the covariates. In Study 1, the well-being of AV drivers was significantly decreased when the level of automation increased in AVs [$M_{\text{in charge}}$=5.2536, $SD_{\text{in charge}}$=1.121, $M_{\text{supervisor}}$=4.2877, $SD_{\text{supervisor}}$=1.313, $M_{\text{not in charge}}$=3.111, $SD_{\text{not in charge}}$= (1.689), $F (2,644)$ =224.187, $P<0.001$]. Then, Tukey's post-hoc analysis was carried out to indicate which groups are significantly different. We found that there is a significant difference between all pairs. Our results show that although AVs expect to increase the well-being of AV drivers [17], the public still feels higher levels of automation during a driving experience will cause higher levels of stress. Only gender as a covariate did exert a significant influence on well-being [F (1,987)=10.166, P<0.001].

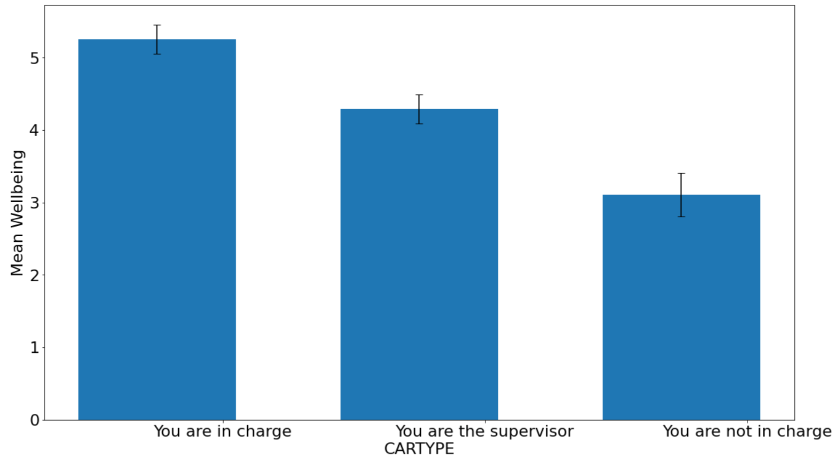

Figure 2: Estimated marginal means of well-being across three levels of AVs automation

Study 2

To examine H2-H4, we performed three moderation analysis models using Hayes's PROCESS Macro-Model 1 [28]. Car type ['*You are in charge*', '*You are the supervisor*', '*You are not in charge*'] acted as the independent variable (X); Uncertainty types acted as moderators in our three models (W1, W2, W3); the well-being of the participant during the driving situation acted as separate dependent variable (Y). Table 4 summarises the results.

Table 4: unconditional interaction of X*W1, X*W2, and X*W3 by uncertainty level. A starred * p-value indicates a significant result.

Model	R2	Significant	Unconditional direct effects at different levels of moderator [95% CI]			
			Uncertainty level	Effect	p-value	95% CL
Unconditional direct effect X*W1	0.004	F= 12.8696 p< 0.001	Low	-0.1281	0.0420*	[- 0.2516, - 0.0046]
			Medium	0.0385	0.3858	[- 0.0486, 0.1256]
			High	0.2051	0.0018*	[0.0765, 0.3336]
Unconditional direct effect X*W2	0.007	F= 22.0180 p< 0.001	Low	-0.2985	0.0001*	[- 0.4423, - 0.1547]
			Medium	-0.0618	0.2404	[- 0.1651, 0.0415]
			High	0.1748	0.01*	[0.0325 , 0.3171]
Unconditional direct effect X*W3	0.006	F= 18.8542 p< 0.001	Low	-0.2017	0.0021*	[- 0.3299, - 0.0735]
			Medium	-0.0106	0.8275	[- 0.1057, 0.0846]
			High	0.1806	0.0064*	[0.0509 , 0.3102]

Study 2.A

As shown in Table 4, there was a direct and significant influence of the level of automation on wellbeing moderated by effect uncertainty ($X*W_1 \rightarrow Y$) [F (1, 9000) =12.8696, p = 0.001)]. Participants who were exposed to lower levels of automation have shown a significant well-being drop when the level of effect uncertainty increased [Effect = -0.1281, p<0.05]. Participants who experienced driving scenarios of low effect uncertainty demonstrated significantly positive well-being reactions (M = 4.2981; SD = 1.117) than those who were exposed to higher effect uncertainty (M =4.0419; SD =1.151). However, this pattern has significantly changed at the higher level of automation scenarios [Effect = -0.2051, p<0.05]. Participant's well-being increased significantly when the level of effect uncertainty increased. Participants in the low effect uncertainty condition demonstrated significantly lower well-being (M = 3.3693; SD =1.29) compared to those high effect uncertainty (M = 3.7795; SD =1.244). Finally, our results showed that increasing the level of effect uncertainty has no effect on participants well-being when participants were exposed to '*You are the supervisor*' car. Figure 3 shows participants well-being responses across three levels of automation ['*You are in charge*', '*You are the supervisor*', '*You are not in charge*'] categorised by level of effect uncertainty.

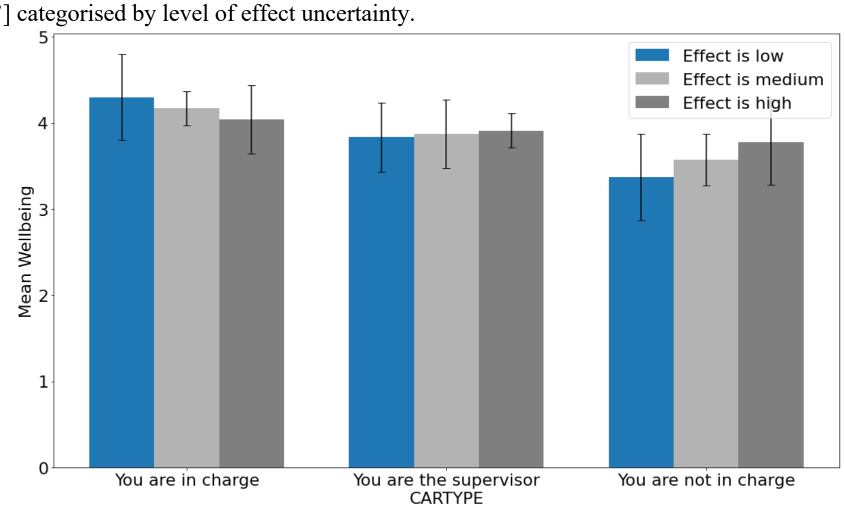

Figure 3: Participant's well-being based on the interaction between Car type and effect uncertainty levels.

Study 2.B

As shown in Table 4, the level of automation had a direct and significant impact on well-being, with response uncertainty acting as a moderator ($X*W_2 \rightarrow Y$) [F (1, 1017) =22.0180, p = 0.001)]. When the level of response uncertainty rose, those who had been exposed to lesser levels of automation demonstrated a significant decline in well-being [Effect = -0.2985, p<0.001]. Participants who were exposed to low response uncertainty exhibited much more positive feelings of well-being (M = 3.8754; SD = 1.247) than those who were exposed to higher response uncertainty (M =3.2785; SD = 1.239). Similar to effect uncertainty, this pattern has significantly changed at the higher level of automation scenarios [Effect = 0.1748, p<0.05]. Participants' well-being increased significantly when the level of response uncertainty increased. Participants in the low response uncertainty group displayed noticeably less well-being (M = 3.4621; SD =1.421) compared to those with high response uncertainty (M = 3.8117; SD =1.325). Our findings also demonstrated that when participants were exposed to higher levels of effect uncertainty in '*You are the supervisor*' car conditions, their well-being was unaffected. Figure 4 shows participants' well-being responses across three levels of automation ['*You are in charge*', '*You are the supervisor*', '*You are not in charge*'] categorised by level of response uncertainty.

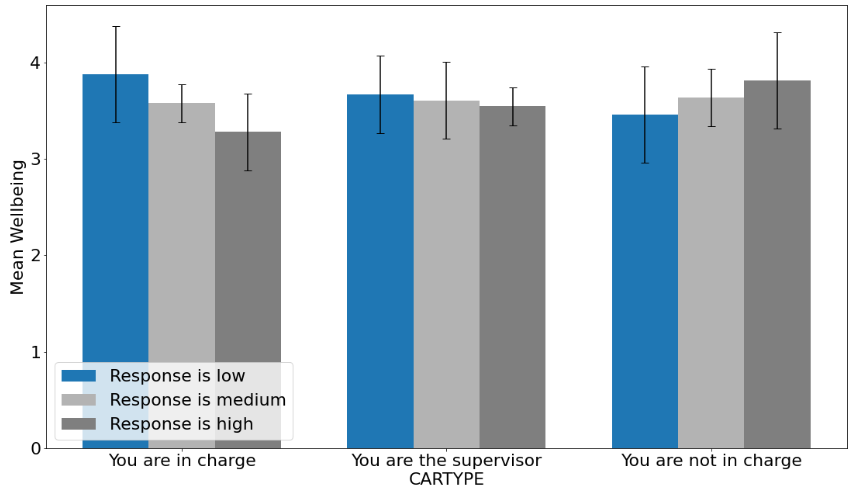

Figure 4: Participant’s well-being based on the interaction between Car type and response uncertainty levels.

Study 2.C

As shown in Table 4, the level of automation had a direct and significant influence on wellbeing, which was moderated by state uncertainty ($X*W_3 \rightarrow Y$) [$F(1, 1047) = 18.5842$, $p = 0.001$)]. Participants exposed to lesser degrees of automation experienced a significant decline in well-being as the level of state uncertainty increased [Effect = -0.2017, $p<0.05$]. Participants with low state uncertainty indicated much more positive feelings of well-being ($M = 4.2138$; $SD = 1.532$) than those who were exposed to higher state uncertainty ($M = 3.8104$; $SD = 1.487$). Like effect and response uncertainty, in scenarios with high levels of automation, this relationship has significantly reversed. [Effect = 0.1806, $p<0.05$]. Participants’ well-being increased significantly when the level of state uncertainty increased. Participants in low-state uncertainty conditions demonstrated significantly lower well-being ($M = 4.1410$; $SD = 1.154$) compared to those with high-state uncertainty ($M = 4.5021$; $SD = 1.122$). Finally, our results showed that increasing the level of state uncertainty does not affect participants' well-being when participants were exposed to ‘*You are the supervisor*’ car. Figure 5 shows participants' well-being responses across three levels of automation [‘*You are in charge*’, ‘*You are the supervisor*’, ‘*You are not in charge*’] categorised by level of state uncertainty.

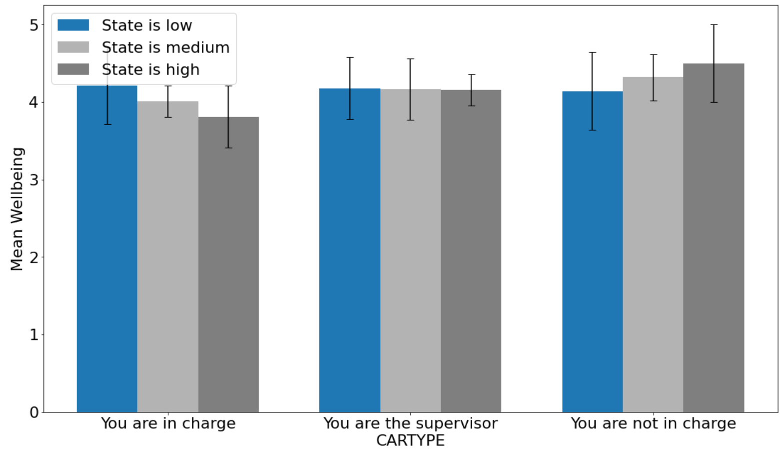

Figure 5: Participant's well-being based on the interaction between Car type and state uncertainty levels.

5 CONCLUSION

Large-scale implementation of AVs has the potential to relieve traffic congestion and provide the public with a higher level of happiness, relaxation and well-being during the driving experience. However, too little is presently known about how AVs are perceived—including the key barriers to their introduction and specifically public well-being responses. This study contributes to the growing literature about AV acceptance and trust using an experimental approach to well-being perception. We are particularly interested in how peoples' well-being responses might change when introducing higher levels of automation and whether perceived uncertainty of the driving scenario can moderate this relationship. Our central finding was that people tend to feel more anxious when higher levels of automation are introduced in the driving experience. However, this trend changed in our data when we introduced our participants to uncertainty scenarios. Participants felt more relaxed at higher levels of automation compared to low levels of automation. This pattern in the data has been found across all uncertainty levels. While there may be many psychological impediments to the adoption of self-driving cars, our key finding leads us to infer that, public reaction to AVs without introducing uncertainty in the driving scenario is likely to be one of them. Despite so, exposing the public to potential scenarios when AVs can be useful was deemed to have an effective approach to changing public well-being perception.

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