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The role of social perceptions on willingness-to-pay for innovations

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ABSTRACT

Innovations might be catalysts for societal progress, driving economic growth, and elevating living standards. By estimating willingness-to-pay (WTP), we can gain insight into the extent to which individuals are willing to adopt innovations. WTP studies so far have estimated *individual* WTP (WTP_I), which refers to the amount individuals are willing to pay for an innovation. We argue that adoption is likely also affected by an individual's perception of how much others are willing to pay, thus setting the standard, which we refer to as *others'* WTP (WTP_O). WTP_O can affect WTP_I, as people may think this is a sensible amount to pay for an innovation (cf. follow social norms). At the same time, WTP_I can influence WTP_O, because when individuals are not sure about what others prefer, they may rely on their own preference as a proxy. Hence, WTP_I and WTP_O are likely to mutually influence each other. Yet, studies have not considered the role of WTP_O. We extend the literature by also accounting for WTP_O in the estimation of WTP. As a case in point, we focus on WTP for automated vehicles (AVs). Results reveal that WTP_I and WTP_O positively influence each other. Further, we examined which factors affect WTP, and found that the overall WTP (i.e., the strength of the correlation between WTP_I and WTP_O) is higher among certain population segments, such as current electric vehicle users and people with a higher level of innovativeness. Interestingly, overall WTP is more strongly affected by WTP_O than WTP_I, indicating that the perception of how much others will be willing to pay may have a greater impact on the adoption likelihood of an innovation than the perception of our own willingness to pay.

1. Introduction

1.1. Willingness to pay for innovations

Innovations might be catalysts for societal progress, driving economic growth, elevating living standards, and addressing pressing challenges (Perez, 2003). From important medical discoveries to easy-to-use technologies, good innovations are expected to enhance quality of life while advancing social inclusion and global connectivity (Spanakis et al., 2016). Yet, good innovations will only achieve their full potential when they are widely adopted. Therefore, it is important to understand which factors affect individuals' willingness to adopt innovations. One relevant indicator of willingness to adopt an innovation is Willingness-To-Pay (WTP) (Breidert et al., 2006).

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WTP reflects the maximum price an individual would be prepared to pay (or to pay extra) in adopting and embracing innovative products, services, or technologies (Klingemann et al., 2021). Ascertaining WTP for innovations typically involves asking individuals how much extra they would be willing to pay for a specific product or service (Breidert et al., 2006; Klingemann et al., 2021), via stated preference methods (Breidert et al., 2006; Klingemann et al., 2021). This approach is believed to mirror trade-offs people make in real-life and offers an easy, fast, and comparatively cheap means of assessing WTP (Klingemann et al., 2021). Framing the question in terms of an additional cost encourages respondents to evaluate the incremental value of the innovation compared to the price of the regular product, thereby considering their available budget. Notably, in line with classic economic models, studies thus far have measured *individual* WTP, which refers to the amount individuals are willing to pay for an innovation.

1.2. The role of others' WTP

We argue that individuals' willingness to adopt innovations not only depends on their *individual* WTP (WTP_I) but may also be affected by an individual's perception of how much others are willing to pay for the innovation, which we refer to as *others'* WTP (WTP_O). Our reasoning is based on social norm theories (e.g. Cialdini & Trost, 1998; Keizer and Schultz, 2018; Steg et al., 2018) that emphasise that our perceptions of what others find important and do may affect our own preferences and behaviour. Indeed, studies have shown that social norm is related to the likelihood that an innovation will be adopted (Nyborg et al., 2016; Huijts et al., 2012; Klöckner et al., 2022). Individuals tend to act in line with the expectations and behaviours of others, particularly those who are important to them: if a particular innovation is seen as socially acceptable, desirable or supported by others, it is more likely to be adopted by individuals. Indeed, people are more likely to adopt an innovation, such as an electric vehicle, when they believe that many others would adopt an innovation in the (near) future (Noppers et al., 2019), that is, when they perceive a strong adoption norm. While this measure can reflect perceived social norms, we clarify that it does not capture societal costs or externalities in the normative sense used in welfare economics. Hence, our concept is distinct from social WTP, for example, conceptualised in health economics (Richardson et al., 2014) and instead builds on psychological theories of social influence and egocentric projection.

We expect a similar social process may play a role in WTP for innovations. Specifically, we theorise that both WTP_O and WTP_I should be considered when aiming to understand WTP for an innovation. Specifically, we expect that WTP_I can be influenced by WTP_O, as people are likely to think that the price others are willing to pay for an innovation is a sensible amount to pay (cf. to follow social norms). At the same time, we hypothesise that *individual* WTP can influence *others'* WTP, as when individuals are uncertain about the amount others are willing to pay for an innovation, they may use their own WTP as a proxy. In other words, individuals may use their personal WTP as a reference point to assess how much other would be WTP. Hence, we assume a bidirectional relationship between WTP_I and WTP_O.

In this conceptualisation, overall WTP can be assessed based on the strength of the correlation between WTP_I and WTP_O. A higher positive correlation means a higher overall WTP. In other words, if both WTP_I and WTP_O are evaluated high it means overall WTP is high as well. This implies that overall WTP should be two-dimensional, and each individual is like a point in a two-dimensional space.

In sum, we aim to extend previous studies by not only studying WTP_I, but also WTP_O for innovations, as well as the relationships between both. As a case in point, we examine how individual and others' WTP affect overall WTP for automated vehicles (AVs). AVs have attracted significant interest, partly due to industry marketing that promotes their potential to improve safety, energy efficiency, and accessibility. In this study, however, we use AVs solely as an illustrative example to test our new WTP framework. This does not imply that we view them as inherently beneficial innovations, as they may also lead to negative consequences such as increased driving and stronger car dependency.

1.3. Automated vehicles (AVs) and individual WTP

The next question is which factors affect overall WPT for AV. We propose that WTP for AV may be related to similar variables, because people may rely on their own preferences to assess what others prefer in uncertain situations, such as with innovations.

Several studies have assessed the WTP_I for AVs (level of 3 or higher according to the SAE taxonomy of levels of automation) in various countries, including France (Payre et al., 2014), Australia (Schoettle and Sivak, 2014), the United Kingdom (Schoettle and Sivak, 2014), the United States (Bansal et al., 2016; Bansal and Kockelman, 2017, 2018; Daziano et al., 2017; Schoettle and Sivak, 2014), South Korea (Shin et al., 2015), China (Liu et al., 2019; Schoettle and Sivak, 2014), India (Schoettle and Sivak, 2014), Japan (Schoettle and Sivak, 2014), and a multinational study (Kyriakidis et al., 2015).

Some of these studies also examined predictors of WTP_I for AV. It has been shown that WTP_I for AVs may be related to several factors, including demographic and socioeconomic status, such as gender, age, income, and education levels, individual beliefs and opinions regarding the innovation, perceptions of safety and risk with respect to the innovation, and personal innovativeness.

Generally, women are less likely to adopt AVs than men and are willing to pay less for AVs (Bansal et al., 2016). Generally, younger individuals are willing to pay more for in-vehicle technologies and features, express a higher interest in automation and a greater willingness to pay for AVs than a conventional vehicle (Bansal et al., 2016). Higher income is typically associated with higher WTP for AVs (Bansal et al., 2016; Kyriakidis et al., 2015), probably because individuals with higher incomes have more financial resources to acquire AV. People with a higher education level are more willing to pay for AV (Kyriakidis et al., 2015). Studies have also demonstrated a positive correlation between owning an electric vehicle and the likelihood of AV purchase (Behnood et al., 2022). From this observation, we postulate that individuals who have already embraced electric vehicles as a mobility innovation might also invest in AVs.

Favourable attitudes towards AV, which are based on perceived risks, costs and benefits of AV, may impact WTP for AVs. Indeed, studies employing the Technology Acceptance Model (TAM) revealed that WTP for an AV and intention to use AV tend to be higher when people think AVs enhance driving efficiency, and when they are believed to be more convenient and easier to use (Karami et al., 2022; Benleulmi & Blecker, 2017. Further, higher perceived safety and lower perceived risks of AV are related to stronger intention to drive AV and higher WTP for AVs (Karami et al., 2022; Liu et al., 2019; Robertson et al., 2017). Personal innovativeness that refers to the inclination of individuals to adopt new technologies earlier than others (Mehdizadeh et al., 2025) can also play a role in shaping AV preferences and WTP, with more innovative individuals exhibiting stronger intentions to use and pay for AVs (Benleulmi & Blecker, 2017).

1.4. Current study

Based on the considerations outlined above, we aim to test a comprehensive approach to estimate WTP for AV. According to our earlier reasoning on social process, we first hypothesise that a higher WTP_O is related to a higher WTP_I and vice versa (H1). Of note, one might argue that a strong degree of alignment between WTP_I and WTP_O can be expected. The fact that WTP_I strongly influences WTP_O has already been indicated as, for example, Ross et al. (1977)'s false consensus effect. Also, Epley et al. (2004) suggest that egoistic anchoring is subject to change. In other words, individuals may project their own values onto others (false consensus effect) or adjust their own valuations based on social expectations (anchoring) (Ross et al., 1977; Epley et al., 2004).

That said, as for the adoption likelihood, an overall WTP – the strength of correlation between WTP_I and WTP_O – can be still estimated. As for the AV adoption, if both WTP_I and WTP_O are high in magnitude, it suggests a high willingness and adoption likelihood of AVs. In this case, it is likely that the AV is perceived as having value for both self and others. Therefore, the WTP can be a point represented by an ordered pair (WTP_O, WTP_I) of numbers in a two-dimensional Euclidean space. This point (WTP) can enhance the ability to capture the potential adoption of innovations by estimating WTP_I and WTP_O for each person.

Next, we examine which factors are related to WTP_I and WTP_O for AV. Based on the above, we test the following hypotheses:

H2 – Individuals who perceive AV as having higher driving efficiency and more convenient, will exhibit a higher overall WTP for AVs.

H3 – Individuals who perceive AVs as safer will display a higher overall WTP.

H4 – Higher personal innovativeness is associated with higher overall WTP for AVs.

H5 – Younger age, higher education, higher income levels, and owning electric vehicles will be associated with higher overall WTP for AVs.

H6 – People who prefer higher levels of AVs report higher overall WTP. Intuitively, this hypothesis aligns with the idea that preferences for a higher AV level reflect perceived value, quality expectations, trust in technology, desire for advanced features, and the anticipation of a more future-proof investment, all of which can collectively influence a higher WTP.

H7 – We posit an additional hypothesis suggesting that media influence and adoption rates can be integral factors contributing to an augmented WTP. Notably, the impact of these variables has not been thoroughly examined in previous research. In contemporary times, social media stands as a pervasive source of inspiration and information, shaping individual perspectives and influencing willingness. Considering the pervasive influence of social media on public opinions and trends, it is reasonable to hypothesise that media exposure and adoption rates may influence individuals' valuation of innovative technologies, thereby potentially enhancing their WTP.

2. Method

2.1. Data

In November 2021, an online survey was conducted among 1000 Norwegian driving license holders, who were selected from a survey panel using random sampling. Stratification by gender, age, and region was conducted, and data was collected from all 11 counties in Norway. Data confidentiality was ensured, and participation in the survey was voluntary. There were 51 % females among the sample, and 7 % were between 18–22 years old, 22 % between 23–35 years old, 39 % between 36–55 years old, and the remaining participants were over 55 years old (Table 1). Norway's population characteristics are similar to those of the sample, according to Statistics Norway (2021). Additionally, our sample was distributed geographically in line with Norwegian population statistics.

2.2. Measures

2.2.1. Willingness to pay

Using the contingent valuation method, individual and social WTP were assessed by asking two questions: (i) "how much *extra* would you be willing to pay for high[1] automatization in a future car in comparison to a car without automatization?" And (ii) "how much *extra* would other people in your social network be willing to pay for high automatization in a future car in comparison to a car

[1] Level 4 SAE. Explanations for the various levels of AVs were provided in the survey as follows: In the hierarchy of driving automation levels outlined by the Society of Automotive Engineers (SAE), Level 4 is identified as "high automation". SAE levels 0 to 4 illustrate the progression of vehicle automation. Level 0 involves no automation, Level 1 provides driver assistance, Level 2 enables limited self-driving, Level 3 handles specific conditions autonomously with a standby driver, and Level 4 achieves high automation in predefined scenarios.

Table 1
The survey sample and the population.

Characteristic	Sample	Population[1]
Age		
The average[2]	47.67	48.46
18–22	7 %	8 %[2]
23–35	22 %	22 %
36–55	39 %	34 %
>= 56	32 %	36 %
Sex		
Male	49 %	50.2 %[2]
Female	51 %	49.8 %
Education		
Holding university degree (highly educated)	50 %	40 %[3]
Income		
Median income (P50% or less)	57 %[4]	43 %[5]
P70% or more	n.a	45 %
EV experience		
EV ownership	30 %	20 %[6]

1. Statistic Norway (ssb.no/en).
2. People who are at least 18 years old.
3. Statistic Norway does not have information regarding the educational level of many immigrants.
4. By comparing respondents' income in an interval scale with the Norwegian average, the income of respondents was indirectly evaluated.
5. The census excludes students' households and children under 18 who live alone.
6. Norway's electric vehicle fleet is expected to reach 20% by 2022. In just under two years, electric vehicles will account for 30 % of the total fleet, according to the Norwegian Electric Vehicle Association.

without automatization?" The contingent valuation is one of the well-established and validated methods for measuring WTP (see Elvik, 2020). The answers to these two WTP items were recorded in Norwegian krone (NOK), and for the purpose of the analysis, they were converted into US dollars (USD) using the following exchange rate: 1.00 Norwegian Krone = 0.095 USD. Descriptives of both WTPs can be found in Section 3.1.

2.2.2. Covariates

To evaluate the TAM factors, measures were used based on previous studies (Buckley et al., 2018; Karami et al., 2022). PU was evaluated using the following three items on 5 points Likert scale: "Highly automated cars will be…[a lot less fuel efficient; less fuel efficient; neither less nor more fuel efficient; more fuel efficient; a lot more fuel efficient]", "If I use a highly automated car my commuting will be …[a lot more stressful; more stressful; neither more nor less stressful; less stressful; a lot less stressful]", and "When it comes to highly automated cars, the status in society of being able to drive a car will be …[much lower; lower; neither lower nor higher; higher; much higher]". The items formed a reliable scale, so mean scores were computed (M = 3.09, SD = 0.89, Cronbach's alpha = 0.63).

PEU was assessed using three statements (the scale's M = 3.14, SD = 1.05, Cronbach's alpha = 0.70) as follows: "Learning to use a highly automated car will be…[a lot more difficult; more difficult; neither more difficult nor easier; easier, a lot easier]", "When I use a highly automated car, I can rely on the car to…[a lot lesser extent; lesser extent; neither lesser nor greater extent; greater extent; a lot greater extent]", and "When it comes to highly automated cars, using them requires the driving training for drivers to be…[much less advanced; less advanced; neither less nor more advanced; more advanced; much more advanced]".

The level of personal innovativeness was measured using the following three items (the scale's M = 2.58, SD = 1.15, Cronbach's alpha = 0.82), including, "If I heard about a new vehicle technology, I would look for ways to try it out", "Among my peers, I am usually the first to try out new vehicle technologies.", and "I like to experiment with new vehicle technologies". The respondents rated their agreement on a five-point Likert scale that ranged from "strongly disagree" to "strongly agree". The items have been included in prior research (Chen and Yan, 2019).

Perceived safety of using highly AVs was assessed with the following item: "When I use a highly automated car in comparison to driving a conventional car, I am worried about being involved in an accident … [a lot more often; more often; neither more nor less often; less often; a lot less often]" (M = 3.11, SD = 0.88).

Susceptibility to media influence as measured with the following item: "To what extent does the mass media (newspapers, magazines, TV, radio, internet, etc.) influence your desire to buy a highly automated car?" (M = 2.21, SD = 1.08). Also, adoption threshold was measured as follows: "To what extent do people in your social network influence you in using a new product?" (M = 2.38, SD = 1.04) Participants evaluated these questions on a five-point Likert scale from (1) "none" to (5) "a lot".

To assess preference with regard to the level of AVs, we asked: "In general, which level of automisation would you prefer for your future car?" Respondents selected a level from level 0 to level 4 SAE. A short description of the levels was provided as follows: SAE levels 0 to 4 illustrate the progression of vehicle automation. Level 0 involves no automation, Level 1 provides driver assistance, Level 2 enables limited self-driving, Level 3 handles specific conditions autonomously with a standby driver, and Level 4 achieves high automation in predefined scenarios.

We further collected information on the respondent's age ("How old are you?"), gender ("What is your gender?"), education level ("What is the highest level of education you have completed?"), income level ("How is your annual income compared to the average in Norway (587,600 NOK)?"), and EV ownership status ("Do you have access to an electric car?").

2.3. Modelling approach

According to our theoretical reasoning, estimation of WTP can be depicted as a multi-equation system. We need a modelling system in which independent variables explain the $\mathrm{WTP_I} - \mathrm{WTP_O}$ relationship. Firstly, we explain how such a system mathematically works.

As illustrated in Fig. 1, consider the system of endogenous variables, denoted by WTP_I and WTP_O, and i exogenous variables, denoted by $X_1, X_2, \ldots, X_i$. The system can be modelled as a set of two main equations, where the endogenous variables are linearly related to the exogenous variables and each other, along with an error term (Wiśniewski, 2023):

$$WTP_I = \alpha_1 + \beta_1 \widehat{WTP}_O + \gamma_{11}X_1 + \gamma_{12}X_2 + \cdots + \gamma_{1i}X_i + u_1 \tag{1}$$

$$WTP_O = \alpha_2 + \beta_2 \widehat{WTP}_I + \gamma_{21}X_1 + \gamma_{22}X_2 + \cdots + \gamma_{2i}X_i + u_2 \tag{2}$$

where α_1 represents the intercept, β_1 is the coefficient of the endogenous variable $\widehat{WTP}_O$, and γ_{11} to γ_{1i} are the coefficients of the exogenous variables X_1 to X_i, respectively. The error term is represented by u_1. α_2 represents the intercept, β_2 is the coefficient of the endogenous variable $\widehat{WTP}_I$, and γ_{21} to γ_{2i} are the coefficients of the exogenous variables X_1 to X_i, respectively. The error term is represented by u_2.

The objective is to estimate the parameters of this system using a two-stage least squares (2SLS) approach.[2] To do so, we identify k instruments for the endogenous variables. These instruments are exogenous variables that are correlated with the endogenous variables but are not included in the equations directly (Wiśniewski, 2023). Instruments are exogenous variables that address potential endogeneity problems.

In the first stage, we estimate the following reduced-form equations:

$$\widehat{WTP}_O = \delta_1 + \lambda_1 Z_1 + \lambda_2 Z_2 + \cdots + \lambda_k Z_k + \eta_1 \tag{3}$$

$$\widehat{WTP}_I = \delta_2 + \lambda_3 Z_1 + \lambda_4 Z_2 + \cdots + \lambda_{(k+2)} Z_k + \eta_2 \tag{4}$$

where $Z_1, Z_2, \ldots, Z_k$ are the k instruments for the endogenous variables, and $\delta_1, \delta_2, \lambda_1, \lambda_2, \ldots, \lambda_{(k+2)}$ are the coefficients on the instruments.

In the second stage, we use the predicted values from the first-stage regressions (reduced forms) as instruments in the second-stage regressions. Specifically, we replace $\widehat{WTP}_O$ and $\widehat{WTP}_I$ with their predicted values from Eqs. (3) and (4), respectively, in Eqs. (1) and (2). This 2SLS approach ensures consistent and efficient estimates of the parameters, even in the presence of endogeneity and omitted variable bias (Mehdizadeh et al., 2023). Finally, the population average of the parameters was used to determine the WTP_I and WTP_O.

3. Results

3.1. The relationship between individual and others' WTP

We theorised that there could be a mutual relationship between *individual* and *others'* WTP, and that if both WTPs are high in magnitude, the adoption likelihood is high. According to this theoretical reasoning, therefore, we avoid interpreting one-dimensional descriptives for the individual and others' WTP. In other words, a stationary point as a $\mathrm{WTP_I}$-$\mathrm{WTP_O}$ pair in the two-dimensional Euclidean space, instead, captures better the relationship between these two aspects. There are several points ($\mathrm{WTP_I}$-$\mathrm{WTP_O}$ pairs) that may have a high $\mathrm{WTP_I}$ and low $\mathrm{WTP_O}$ or vice versa (see Fig. 2). Thus, in this case, one-dimensional descriptive analysis can be misleading, ignoring the influence of another aspect. For example, even though about 10 % of participants are reporting $\mathrm{WTP_I} > 1000$ USD, their $\mathrm{WTP_O}$ was 0. While around 6 % of respondents reporting $\mathrm{WTP_O} > 1000$ USD, their $\mathrm{WTP_I}$ was 0.

[2] Furthermore, we tested the robustness of the regression results (each equation) by employing a Tobit regression in addition to the least squares estimation method. This was done in order to address the possibility of left-censored data (i.e., several participants have zero WTP for self or others). The two models yielded similar results, i.e., convergent results for the significant predictors of both WTPs. Therefore, we stick with least squares estimation since it offers a better fit with the two-stage least squares (2SLS) estimation methodology for the multi-equation model. Studies estimating WTP for AVs have also reported that these two types of models yielded similar results, so choosing one of them would be sufficient (Liu et al., 2019).

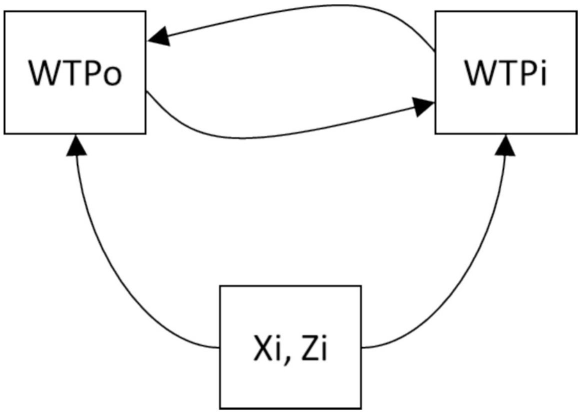

Fig. 1. The multi-equation econometric system estimating WTP_I-.WTP_O

To investigate the relationship between WTP_I and WTP_O, a two-dimensional scatter plot was utilized, which is a graphical representation shown in Fig. 2. This plot shows how the two variables are related, with the WTP_O value shown on the x-axis and the WTP_I value shown on the y-axis. Fig. 2 shows that about 7.1 % of the data points correspond to the range of $WTP_O < 5506$ USD and $WTP_I \geq 6209$ USD. Approximately 6.2 % of the data points correspond to the range of $WTP_O \geq 5506$ USD and $WTP_I < 6209$ USD. Generally speaking, the scatterplot shows that separate and isolated analysis of each of *individual* and *others'* WTP can lead to different interpretations of the WTP. For several respondents, even though they report a high *individual* WTP, the *others'* WTP is very low, and vice versa.

The shape of the scatter plot can provide insight into the strength and direction of the relationship between the variables. If one variable increases as the other increases, a positive relationship is suggested, which is represented by an upward slope from left to right on the scatter plot. A correlation analysis revealed a strong positive correlation between WTP_I and WTP_O ($r = 0.74, p < 0.001$). This strong correlation may, in part, be explained by well-documented psychological mechanisms. For instance, the false consensus effect (Ross et al., 1977) suggests that people tend to assume others share their values and preferences, potentially inflating WTP_O based on their own WTP_I. Similarly, egocentric anchoring (Epley et al., 2004) describes how individuals anchor on their own preferences when

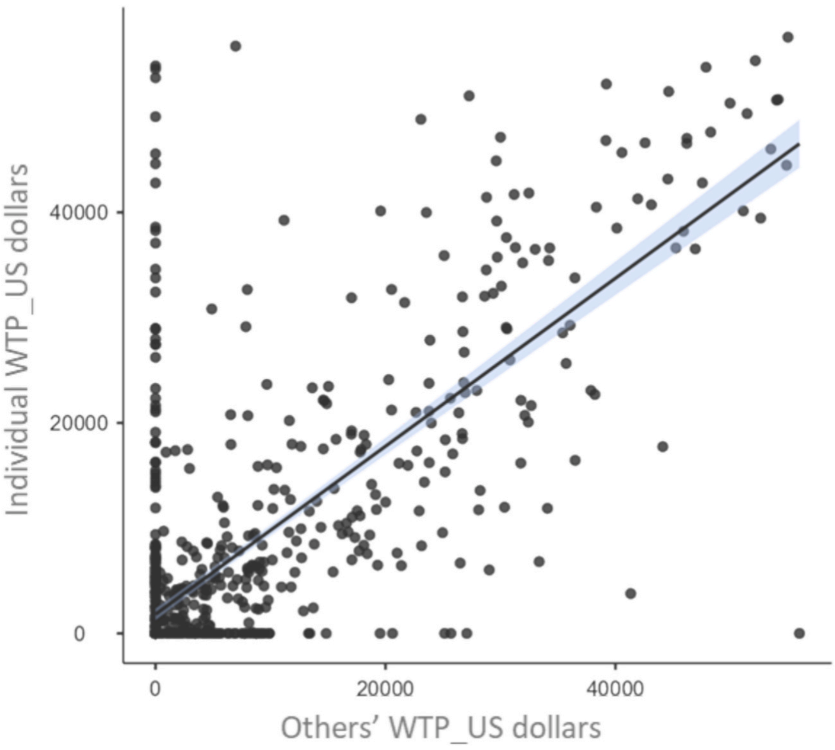

Fig. 2. Scatterplot of the relationship between *individual* and *others'* WTP.

estimating others' intentions, adjusting insufficiently from this anchor. Additionally, it is important to note that this correlation does not prove causation, as other factors may also be influencing the relationship between WTP_I and WTP_O. To investigate further, a multi-equation model might be required to rule out other potential influencing factors.

3.2. Factors related to individual and others' WTP (WTP_I-WTP_O)

The final model was estimated based on the developed theoretical framework in the Introduction and illustrated in Fig. 1. Two other requirements were also considered: (1) all variables in the first-stage regressions (reduced forms) and in the second-stage regressions should be statistically significant at 95 % CI, and (2) relevant predictors should be tested in the reduced-form models for explaining WTP_I and WTP_O. This model examines the role of different independent variables on the WTP_I-WTP_O relationship.

Table 2 shows a description of variables that appeared statistically significant in the model. For instance, people in the study were on average 47.67 years old. Around 52 % of respondents held a university degree, and around 10 % preferred level 4 AVs, 13.3 % level 3, 43.4 % level 2, 16.4 % level 1, and the rest level 0. The significance of certain exogenous variables did not manifest in the model with the original measurement scale, attributed to imbalanced data distributions. Accordingly, we tested the variables in multiple formats, encompassing continuous, ordinal, nominal, and dummy variables.

In Table 3, considering the effect of WTP_O on WTP_I, the results of the multi-equation model that explains WTP_I are presented. In the modelling process, different independent variables were tested as instrumental variables for the endogenous variable (WTP_O) and as exogenous variables for WTP_I. Following the testing of different combinations of variables, we found that a higher *individual* WTP is a direct function of a higher $\widehat{WTP}_O$ ($p < 0.001$) and AV level preferences ($p < 0.05$). $\widehat{WTP}_O$, as the instrumented endogenous variable here, was predicted significantly by seven variables, notably Age, HighIncome, EVExe, Risk, Choice, Media, and Adoption in the reduced-form equation, at the same time. The model fitted the data well ($Wald\ chi^2(2) = 534.57,\ Prob > chi^2 < 0.001$), and the variables explained 52 % of the variance in the WTP_I. The first-stage F-statistic (F = 37.25) exceeds the conventional threshold of 10 (Staiger & Stock, 1997), and the Cragg–Donald Wald F-statistic (37.25) surpasses all Stock–Yogo (2005) critical values, including the 5 % maximal IV[3] relative bias threshold of 19.28. This confirms that our instruments are strong. Based on these results, we conclude that our 2SLS estimates are robust and reliable.

Considering the effect of WTP_I on WTP_O, Table 4 presents the results of the multi-equation model that accounts for WTP_O. The model shows that a higher *others'* WTP is a direct function of a higher $\widehat{WTP}_I$ ($p < 0.001$), higher EVExe ($p < 0.05$), and Risk ($p < 0.05$). $\widehat{WTP}_I$ was predicted significantly by nine instrumental variables including Age, Female, WellEdu, HighIncome, EVExe, PU, PEU, Innovat, and Choice in the reduced-form equation, simultaneously. The model fitted statistically significant ($Wald\ chi^2(3) = 513.96,\ Prob > chi^2 < 0.001$), and the variables explained 56 % of the variance of the WTP_I. The first-stage F-statistic is 28.32, well above the conventional threshold of 10. Furthermore, the Cragg–Donald Wald F-statistic (28.32) exceeds the Stock–Yogo critical values for relative bias at all levels (e.g., 5 % = 20.25, 10 % = 11.39). While it falls slightly below the size distortion threshold of 33.84, it remains in a range considered strong in applied research. Therefore, we conclude that our instruments are strong and valid, and that our 2SLS estimates are robust.

The average of the variables in the sample was used to determine the WTP_I and WTP_O. Based on a level of WTP_O and other parameters, Eq. (5) estimates the WTP_I level (on a sample average). In the same manner, Eq. (7) provides us with an estimation of what the WTP_O level would be if we were given the WTP_I level and other variables. Consequently, a stationary point is a pair of WTP_I-WTP_O which would be calculated on the basis of its own level.

$$WTP_I = 1.01\,\widehat{WTP}_O + 688.08Choice - 1308.39 \tag{5}$$

$$\widehat{WTP}_O = -130.96Age + 2106.57HighIncome + 3296.79EVExe + 6628.93Risk + 953.44Choice + 1088.72Media + 1475.49Adoption + 1516.35 \tag{6}$$

$$WTP_O = .799\,\widehat{WTP}_I + 1532.73EVExe + 4054.21Risk + 30.375 \tag{7}$$

$$\widehat{WTP}_I = -191.03Age + 1432.41Female + 1120.93WellEdu + 2129.72HighIncome + 2402.78EVExe + 6068.88PU - 1849.71PEU + 4654.60Innovat + 2345.90Choice + 6028.77 \tag{8}$$

According to the model's equilibrium, these calculations show that, on average, the maximum amount that an individual would be willing to pay extra for high automatisation in a future car (WTP_I) is 6115 USD. On average, participants in the study also indicated that the maximum amount that others (e.g., family members, peers, friends) in their social network would be willing to pay extra for high automatisation in a future car (WTP_O) is 5496 USD.

[3] Instrumental Variable.

Table 2
The description of variables appeared statistically significant in the model.

Variable	Descriptive/scale	Mean	SD
Demographic and socioeconomic			
Age	Ranging from 18 to 80	47.67	16.87
Female	1: The respondent is a female; 0: otherwise	0.51	0.50
HighEdu	1: The respondent has a university degree; 0: otherwise	0.52	0.50
HighIncome	1: The respondent's annual income is greater than the average in Norway (587,600 NOK* or 55,822 USD); 0: otherwise	0.23	0.41
EVExe	1: The respondent experienced EV driving; 0: otherwise	0.30	0.45
AV choice			
Choice	1: Level 0, 2: Level 1, 3: Level 2, 4: Level 3, 5: Level 4	2.83	1.53
AV-related psychological factors			
PU (Perceived Usefulness)	1: The mean score of PU is 4 or greater than 4; 0: otherwise	0.14	0.34
PEU (Perceived Ease of Use)	1: The mean score of PEU is 4 or greater than 4; 0: otherwise	0.28	0.45
Risk	1: The individual perceived safety worries while using AV is 4 or greater than 4; 0: otherwise	0.25	0.43
Innovat	1: The mean score of innovation is 4 or greater than 4; 0: otherwise	0.11	0.32
Media	Likert scale ranging from 1 to 5	2.21	1.08
Adoption	Likert scale ranging from 1 to 5	2.38	1.05

* Average annual earnings in 2020. 1.00 Norwegian Krone = 0.095 USD.

Table 3
The multi-equation econometric model explaining WTP_I.

Second-stage part	Coefficient	Std. err.	z		[95 % conf. interval]	
$\widehat{WTP_O}$	1.01	0.05	17.70	**	0.89	1.11
Choice	688.08	269.30	2.56	*	160.25	1215.91
Constant	−1308.39	696.40	−1.88		−2673.31	56.52
Instrumented: $\widehat{WTP_O}$ Instruments: Age HighIncome EVown Risk Choice Media Adoption						
Reduced-form part	Coefficient	Std. err.	z		[95 % conf. interval]	
Age	−130.96	19.60	−6.68	**	−169.44	−92.48
HighIncome	2106	747.09	2.82	**	640.50	3572.65
EVExe	3296.79	731.60	4.51	**	1861.11	4732.48
Risk	6628.93	2454.78	2.70	**	1811.69	11446.17
Choice	953.44	298.61	3.19	**	367.45	1539.43
Media	1088.72	382.44	2.85	**	338.23	1839.22
Adoption	1475.49	394.09	3.74	**	702.13	2248.86
Constant	1516.35	1520.31	0.31		−1467.08	4499.79

Note: **, * == > significance at 1 % and 5 % level.

4. Findings and discussion

We developed an estimation framework for WTP considering the mutual relationship between *individual* and *others'* WTP since we believed that our perception of how much others are willing to pay is also influential in our own willingness and vice versa. Specifically, we indicated that it is important to consider both *individual* and *others'* WTP. We theorised that if both *individual* and *others'* WTP are high in magnitude, it suggests a high WTP or adoption likelihood. We applied this estimation for the adoption of AVs among a Norwegian population-based sample.

The estimated WTP_I-WTP_O relationship confirmed our theoretical reasoning, showing that (1) there is a very close and positive relationship between WTP_I and WTP_O, and (2) there are certain people (WTP_I-WTP_O pairs) who have a high WTP, i.e., both *individual* and *others'* WTP are high in magnitude, at the same time. On the other hand, some stationary points (WTP_I-WTP_O pairs) have high *individual* WTP but low *others'* WTP (according to Fig. 2), which may lead to a false impression of people's willingness for innovation when relying solely on *individual* WTP estimations. This issue is further illustrated by examining the effect of a relevant predictor, namely AV level preference/choice (ranging from level 0 to 4), on WTP for high automisation. Intuitively, a higher AV level preference is likely to be positively associated with a higher WTP for higher AV levels. As discussed in the following paragraph, this predictor more accurately demonstrates the importance of others' WTP in determining the likelihood of adoption.

When it comes to direct predictors of *individual* WTP while accounting for the WTP_O effect, the results show that people who prefer higher AV levels are more likely to have greater *individual* WTP for AVs. Considering the effect of WTP_O on WTP_I, a one-level increase in preferred AV type will increase *individual* WTP by 688 USD. As shown in Fig. 3a, it is evident that participants with preference for conventional vehicles (level 0) reduce the positive relationship between WTP_I and WTP_O compared with other AV preference groups,

Table 4
The multi-equation econometric model explaining WTP_O.

Second-stage part	Coefficient	Std. err.	z		[95 % conf. interval]	
$\widehat{WTP_I}$	0.79	0.04	16.87	**	0.70	0.89
EVExe	1532.73	610.30	2.51	*	336.56	2728.91
Risk	4054.21	1898.18	2.14	*	333.85	7774.57
Constant	30.37	338.99	0.09		−634.04	694.79
Instrumented: $\widehat{WTP_I}$						
Instruments: Age Female WellEdu HighIncome EVown PU PEU Innovat Choice						
Reduced-form part	Coefficient	Std. err.	z		[95 % conf. interval]	
Age	−191.03	20.72	−9.22	**	−231.70	−150.35
Female	1432.41	679.01	2.11	*	99.94	2764.88
WellEdu	1120.93	570.66	1.96	*	2.43	2239.42
HighIncome	2129.72	826.39	2.58	*	508.01	3751.43
EVExe	2402.78	790.60	3.04	**	851.32	3954.25
PU	6068.88	2146.96	2.83	**	1855.71	10282.05
PEU	−1849.71	790.85	−2.34	*	−3401.67	−297.75
Innovat	4654.60	1147.82	4.06	**	2402.13	6907.08
Choice	2345.90	311.54	7.53	**	1734.52	2957.27
Constant	6028.77	1467.12	4.11	**	3149.70	8907.83

Note: **, * == > significance at 1 % and 5 % level. WellEdu.

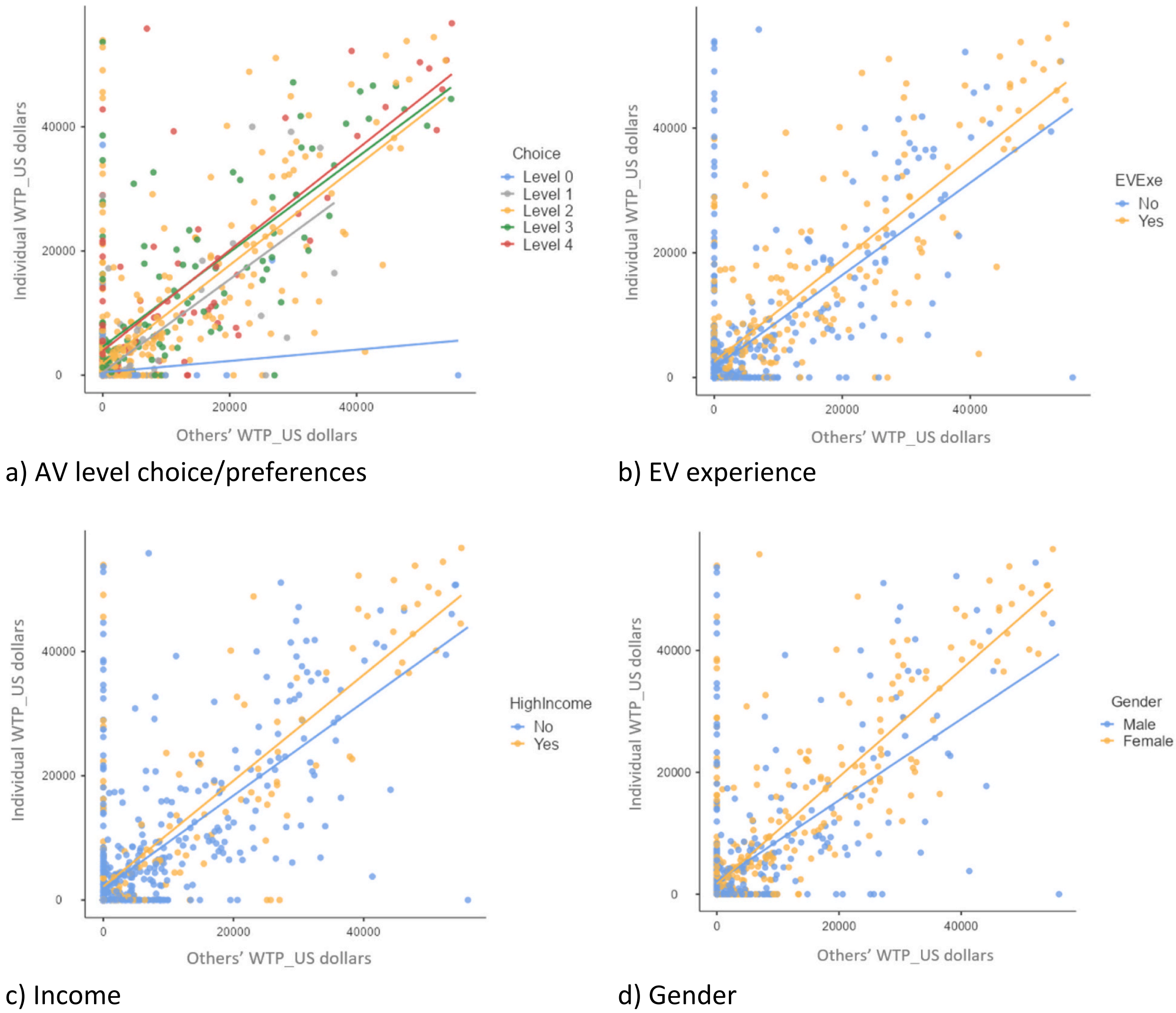

Fig. 3. The role of some exogenous variables on the relationship between WTP_I and WTP_O.

resulting in a dramatic decrease in the value of *individual* WTP when there is an increase in *others'* WTP, as opposed to when groups with other AV level preferences are present. Among the different AV preference groups, people in level 4 group result in WTP_I-WTP_O pairs which are most likely to be in the higher adoption group. As we move from level 0 to level 4, the positive relationship between WTP_I and WTP_O strengthens. In other words, if both *individual* and *others'* WTP for AVs are at their highest values it is likely that the people also have strong preferences for AV level 4. From a technical perspective, this finding supports the notion of considering both *individual* and *others'* WTP in the context of mutual relationships. Theoretically, this finding also suggests that people who prefer manual cars (not automated ones) perceive that their social network is more willing to pay for AVs than they are.

We found that WTP or adoption likelihood depends on an individual's own willingness and the perceived willingness of others. When considering the multi-equation equilibrium, marginal effects indicate that, if WTP_O increases by 1 USD, WTP_I will increase by 1.01 USD, ceteris paribus. In the meantime, an increase in WTP_I by 1 USD results in an increase in WTP_O by 0.79 USD, ceteris paribus. As a result of this finding, the WTP is more influenced by WTP_O than by WTP_I. In other words, the perception of how much others will be willing to pay has a greater impact on the likelihood of adoption than the perception of our own willingness to pay. This finding highlights the role of social norms in estimating adoption likelihood or willingness to pay for innovation topics.

As expected, the results show that the so-called "overall WTP," which is based on a strong mutual effect between WTP_I and WTP_O, may reflect the respondents' underlying psychology. Specifically, it may indicate how much they are influenced by social cues or internal judgments at the time of the survey. This may involve psychological effects such as the false consensus effect (Ross et al., 1977) and egocentric anchoring (Epley et al., 2004). These findings can provide useful insights for marketing and pricing strategies based on customer segmentation. For example, if a person's WTP_I is higher than their WTP_O, marketers can focus on increasing the perceived personal value of the product by highlighting its personal utility or individual safety. On the other hand, if WTP_I is lower than WTP_O, marketers can use social proof or peer influence to raise WTP_I. By adjusting communication strategies based on the gap between WTP_I and WTP_O, companies may be able to encourage adoption of new products or innovations more effectively.

As described in Table 5, to get a better idea of how different variables in the model influence the WTP (i.e., the mutual relationship between WTP_I and WTP_O), several scenarios are developed. Different scenarios regarding different variables (from A to O in addition to Model Equilibrium (ME)) in the model were defined. As for the AV preference, for example, on average, if all participants preferred AV level 4 (scenario A), their *individual* WTP and *others'* WTP would be 8047 USD and 7699 USD, respectively. On the other hand, if all preferred AV level 0 (scenario E), their *individual* WTP and *others'* WTP would be 3093 USD and 2075 USD, respectively. As illustrated in Fig. 4, scenario A again shows that the average WTP (the equilibrium point) will significantly increase for people with preference for AV level 4 compared to business-as-usual (average Model Equilibrium (ME) point).

When it comes to predictors of *others'* WTP while accounting for the WTP_I effect, the findings indicate that EV experience and higher safety perceptions regarding AVs will increase the level of WTP_O. Fig. 3b shows that participants with EV experience demonstrate a stronger positive WTP_I-WTP_O relationship, implying a higher WTP. In addition, the scenario analysis indicates that the equilibrium point will move from ME to H (a point with higher WTP) if all participants had EV experience (Fig. 4). In this case, it could be explained by the fact that most EV-experienced individuals drive modern cars with at least level 1 automatization, often level 2. Respondents with high safety perceptions regarding AVs (scenario I) will noticeably increase the WTP (from ME to I in Fig. 4). In other words, safety perception has the biggest impact on WTP of AV among the tested variables. When individuals feel confident about the safety of AVs, they become more inclined to pay a higher price for these vehicles, which, in turn, can lead to a greater diffusion or adoption of highly automated vehicles among the general population. Moreover, this finding aligns with broader trends in the automotive industry. Safety has always been a paramount concern for consumers when adopting new automotive technologies. By highlighting the safety benefits of AVs and addressing any perceived risks or uncertainties, manufacturers and stakeholders can create a positive perception around automated driving and drive higher acceptance and adoption likelihood.

Other variables indirectly influenced WTP (the WTP_I-WTP_O relationship). Older people were WTP less than younger individuals.

Table 5
Scenarios descriptions and estimated WTP_I-WTP_O.

Scenario	Description	WTP_I	WTP_O	$WTP_I - WTP_O$	Pricing/marketing strategy
ME	Model Equilibrium	6115	5496	619	Personal utility
A	If all preferred AV level 4	9698	9573	125	Personal utility
B	If all preferred AV level 3	8047	7699	348	Personal utility
C	If all preferred AV level 2	6396	5824	572	Personal utility
D	If all preferred AV level 1	4745	3950	795	Personal utility
E	If all preferred AV level 0	3093	2075	1018	Personal utility
F	One year increase in age	5982	5344	638	Personal utility
G	If all were high income	6115	5926	189	Personal utility
H	If all had EV experience	8462	7930	532	Personal utility
I	If all perceived that highly AVs are safe	12,705	9489	3216	Personal utility
J	If all got the highest media influence	9195	5500	3695	Personal utility
K	If all got the highest adoption	10,036	5500	4536	Personal utility
L	If all were female	6118	6064	54	Personal utility
M	If all had the high PU	6118	10,232	−4114	Social proof
N	If all had the high PEU	6118	4439	1679	Personal utility
O	If all had the high Innovat	6118	8802	−2684	Social proof

Note. All values are in US dollars.

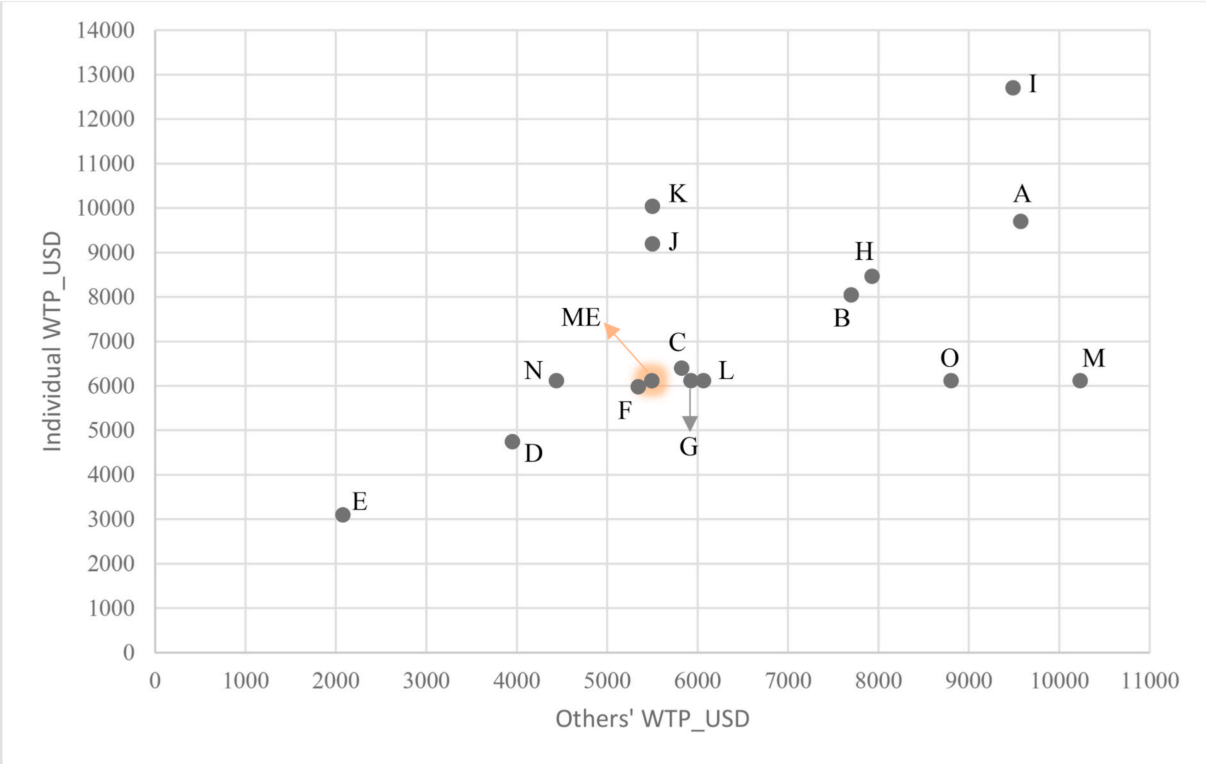

Fig. 4. Estimated WTP_I-WTP_O pairs based on different scenarios (see Table 5 for the description of scenarios).

An increase in age by one year led to a decrease in WTP. As shown in Fig. 4, however, this effect was negligible since the WTP goes from ME to F in the two-dimensional space. A 10-year increase in age could, however, result in a greater decrease in WTP (to a point close to D). As for the role of income, we observe a small improvement in WTP if we assume that all participants are high income (see Fig. 3.c). This scenario (G), however, mostly influenced positively the *others'* WTP dimension, meaning that high-income people perceive that others (in their social network) are willing to pay more for AVs. When it comes to the role of gender in our Norwegian sample, females tend to have a slightly higher WTP than males. For females the positive WTP_I-WTP_O relationship becomes stronger, according to Fig. 3.d.

We found that stronger social media and peer influence can increase the WTP, in which, *individual* WTP dimension was more strongly under the influence of these variables than *others'* WTP. Based on Fig. 4, it can be observed that the equilibrium point of the model goes up after the implementation of scenarios J and K, indicating the influence of such factors on higher *individual* WTP. This finding is in line with past studies in the US (Sharma and Mishra, 2022), Australia (Ghasri and Vij, 2021), India (Dahiya and Gayatri, 2018), and China (Zhu et al., 2020) emphasising the impact of social and mass media and peer social networks on AV adoption. However, the interesting result here is that the more individuals are affected by social media and their peer network, the more they increase their individual willingness rather than perceive that their network is willing to pay more.

Regarding the rest of the psychological variables in the model, we found that people with high level of innovativeness and perceived usefulness of highly AVs have higher *others'* WTP than *individual* WTP. According to scenarios M and O, PU and innovativeness cause the equilibrium point of the model to be shifted to the right.

5. Conclusion

Many studies assessed *individual* WTP as an indicator of the likelihood that people would adopt innovations. Even though *individual* WTP offers a glimpse into individuals' own willingness and adoption, real-world adoption is also affected by an individual's perception of how much others are willing to pay which may serve as an anchor for assessing one's own WTP. Accordingly, we developed a framework theorising a mutual influence framework between *others'* WTP and *individual* WTP. We applied this concept to the study of WTP for AVs as an innovation topic in the transport sector. Of note, and as stated earlier, we used AVs solely as a case of innovation to test our framework, and we remain neutral regarding whether they represent a good or bad innovation.

We found that WTP or adoption likelihood depends on an individual's own willingness and the perceived willingness of others. A closer look at our findings reveals that the WTP is more influenced by WTP_O than by WTP_I. In other words, the perception of how much others will be willing to pay has a greater influence on the adoption likelihood than the perception of our own willingness to pay.

We found that *individual* and *others'* WTP (i.e., the extra amount that individuals/significant others would be willing to pay for high automatization in a future car in comparison to a car without automatization) are estimated at 6115 USD and 5496 USD, respectively, for a Norwegian population-based sample. We found that there is a mutual, close, and positive relationship between *individual* and *others'* WTP. Our analysis shows that the overall WTP (the relationship between WTP_I and WTP_S) is estimated higher among people with a preference for highly AVs (SAE level 4), current electric vehicle users, people who think that high AVs are safe, those who are affected by social media, and peers and people with a higher level of innovativeness and perceived usefulness about highly AVs.

As for future research, we encourage researchers in different fields to test the importance of *others'* WTP. Methodologically, we also believe that there is room to understand how we can better estimate overall WTP considering social perceptions. Longitudinal studies are also needed to monitor how perceptions of adoption evolve over time as the technology becomes more integrated into society. This ongoing research will be instrumental in understanding the changing dynamics of *individual* and *others'* WTP as innovations, for example AVs, become a common feature on the transport landscape. It is important to note that our findings do not imply that WTP_I or WTP_O can replace formal cost-benefit analyses for policy evaluation. WTP_O, in particular, reflects perceived social preferences rather than external societal benefits or normative values. Therefore, our approach is best suited for understanding demand-side adoption behaviour, informing communication strategies, or market segmentation, rather than serving as a standalone metric for welfare economics or regulation.

CRediT authorship contribution statement

Milad Mehdizadeh: Idea, Writing – review & editing, Writing – original draft, Visualization, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Christian A. Klöckner:** Writing – review & editing, Validation, Resources, Project administration, Conceptualization.

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.

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Data availability

The data that has been used is confidential.

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