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Are you adopting artificial intelligence products? Social-demographic factors to explain customer acceptance

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ABSTRACT

Are consumers accepting AI-based products? What are the socio-demographics influencing the adoption of these products? This study tests the potential users' social-demographic characteristics that influence the relationship between innovation and AI-based products. The latter are robots (e.g. *chatbots*) and AI (e.g. recommendation systems, amongst others). A mixed methods approach is adopted using both qualitative and quantitative analysis with non-metrical multidimensional scaling (NMDS) to map opinions about digitally-intensive products, such as robots and AI, and the attitude towards innovation. The research uses data on the general population from the Spanish innovation barometer survey ($N = 3{,}005$). Findings show that individuals who have a negative attitude towards innovation have a negative opinion about robots and AI. As regards social-demographic dimensions, age and economic conditions moderate this effect, causing a more positive opinion towards digitally-intensive products amongst young people and individuals with a higher socio-economic level. These effects are increased by the moderating role of sex.

1. Introduction

Artificial Intelligence (AI) can be defined as a complex technology capable of learning and changing its behaviour based on cues from the environment, aiming to simulate human intelligence (Glikson & Woolley, 2020). Robots are devices programmed with AI that can take the form of software, as financial robo-advisors designed to autonomously give financial advice (Méndez-Suárez et al., 2019). Also, they have a physical entity in the form of military robots, including unmanned aerial vehicles, or task robots; industrial robots used in applications such as welding, assembly or material handling; commercial robots as medical and surgical robots; agricultural or construction robots; and in the personal market, robots for entertainment, broadcasting industry (Medina et al., 2022), cleaning, education, security or household applications (Sander & Wolfgang, 2014), marketing applications (Wu & Monfort, 2023), or even human resources management and attraction (Bamel et al., 2022; De Obesso Arias et al., 2023; Montero Guerra et al., 2023). Additionally, a new generation of robots has been designed to achieve symbiosis with humans (Murata et al., 2019; Nomura, 2017). Robotization is an unparalleled digitally-intensive innovation that has proven its many benefits to society (Salvine et al., 2011), which promotes innovation amongst firms, including SMEs (Wongsansukcharoen & Thaweepaiboonwong, 2023), and has a huge impact on the increase in intangible assets (Jankowska et al., 2021). The global turnover of the robot industry has increased from USD 15.1 billion in 2010 to an expected USD 70 billion in 2028 (Placek, 2022). Recent studies have shown great concerns amongst humans regarding the impact of innovative digitally-intensive products on human activity (e.g. Méndez-Suárez & Danvila-del-Valle, 2023); in the United States a survey found that concern doubles enthusiasm about robots in the workplace (Smith & Anderson, 2017), and surveys conducted in Europe found a negative trend in attitudes towards robots amongst the population over the period 2012 to 2017 (Gnambs & Appel, 2019). These are just some of the effects of robots based on AI.

Literature on the adoption of AI by firms in activities such as recruitment (Pan et al., 2022), banking (Windasari et al., 2022) education (Winkler et al., 2020), hospitality and tourism (Leung & Wen, 2020), public services (Ha & Thanh, 2022), firms' sustainable digital transformation (Nyagadza, 2022), extract information from annual reports (Aguado-Correa et al., 2023), to forecast market prices of

Availability of Data and Code for NMDSThe data and R code that support the NMDS findings of this study are openly available in Harvard Dataverse at doi:10.7910/DVN/KMHSBG.

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alternative investments, (Alcázar-Blanco et al., 2021) and the effect of the adoption of AI in firm performance (Heredia et al., 2022) has dramatically expanded in the last few years, in parallel to those sub-lines of enquiry that study customer adoption of AI. Customer adoption literature primarily uses the *technology acceptance model* (TAM; Davis, 1989; Venkatesh & Morris, 2000) and the *unified theory of acceptance and use of technology* (UTAUT) model (Kulviwat et al., 2007). As summarized by Mariani et al. (2023), the drivers of adoption of AI-based products (such as conversation agents) fall into three types: first, those that are linked to product design; second, those related to the users' perceptions of AI-based products; third, contextual and environmental factors. We leave these models to others, as this present study goes further by incorporating sociodemographic variables that also influence technology adoption. In doing so, we theorize and test the inclusion of social and demographic traits on the relationship between new technology and adoption of AI and AI-based robots. As socio-demographics (such as age, sex, or socio-economic conditions of users) influence opinion towards robots and AI (de Graaf & Ben Allouch, 2013; Dinet & Vivian, 2014; Ivanov & Webster, 2019; LaRose & Eastin, 2004; Shibata et al., 2009), we incorporate these potential moderating effects. In addition, we posit that the customers' attitudes towards innovation also influence AI-based product adoption. Our argumentation is based on the fact that, as attitudes towards innovation predict consumers' acceptance of new technologies (Nomura et al., 2008; Song & Kim, 2020), we connect attitudes to innovation to acceptance of new AI-based products, with an additional lens, i.e. attitudes towards innovation, to the socio-demographics to understand AI-based adoption. Our cross-fertilization of sub-lines of enquiry produces a novel approach to understanding consumers' AI acceptance.

Our theoretical framework is related to the positive and negative perceptions about the adoption of AI. Negative perceptions about innovations, on the one hand, include concerns about loss of control and freedom (Meyer-Waarden & Cloarec, 2022), erosion of the personal sense of community and family (Schwab, 2017), loss of traditions and values (Boogaard et al., 2011) which affect social and communication skills (Schwab, 2017), or the replacement of many jobs (Rampersad, 2020), amongst others. These negative opinions, on the one hand, are empirically proved in different industries, such as healthcare. According to Longoni et al. (2019), AI is revolutionizing healthcare, but when researching consumer receptivity to AI in medicine, evidence point out that consumers are reluctant to utilize healthcare provided by AI in real and hypothetical choices. Consumers, therefore, prefer to rely on friends rather than on computerized recommendation systems, placing greater weight on the same advice given by human experts versus that by statistical models (e.g. Önkal et al., 2009). Positive perceptions associated with innovation and technology acceptance, on the other hand, highlight the importance of financial development (Maradana et al., 2019), productivity (Carayannis & Grigoroudis, 2014; Kafetzopoulos et al., 2015) and sustainability (Verheyen & Peterson, 2020).

Overall, our study, as a main goal, explores whether consumers accept AI-based products and how socio-demographic and innovation attitudes affect customers' acceptance of AI-based products. Our goal is operational through two research questions: (1) Are attitudes towards innovation affecting opinions towards AI? (2) Are socio-demographic dimensions affecting consumers' acceptance of AI? To answer these questions, the study uses a mixed methods approach, using non-metrical multidimensional scaling (NMDS) to simultaneously map opinion about these digitally-intensive products and the attitude towards innovation and regression analysis to verify quantitatively the relations found with the mapping of consumers. The research utilizes 3005 observations from consumers, sourced from the Spanish innovation barometer survey.

Regarding the structure of the paper, first, we present a conceptual framework in the field of AI and robots and develop the different hypotheses. Next, data and methods are explained and finally, we present the discussion and conclusions.

2. Conceptual framework

To understand the acceptance of digitally-intensive products such as robots and AI amongst potential users, specific models have emerged in recent years, including models of acceptance of social robots for the elderly (Heerink et al., 2010), socially interactive robots (de Graaf et al., 2019; Shin & Choo, 2011), or robots for care (Turja et al., 2020). According to Pietri et al. (2013), individuals use a process of generalization of attitudes when judging a new or hypothetical situation, weighing the extent to which it resembles related categories positively or negatively. Hence, the disposition of users towards innovation can be generalized and predicts their attitudes towards robots and AI as well as other forms of innovative digitally-intensive products (Fernández-Portillo et al., 2022; Nomura et al., 2008; Song & Kim, 2020). Amongst the negative perceptions associated with innovation, recent studies have shown that some people perceive the fourth industrial revolution as a danger to the personal sense of work, community, family and identity (Schwab, 2017). In addition, several studies have shown that modernity has given way to technological innovation which has encouraged economic progress, but has led to a loss of traditions and values (Boogaard et al., 2011), which will affect social and communication skills (Schwab, 2017). Along with these social aspects, a large number of people fear that innovation will replace many jobs (Rampersad, 2020) due to restructuring in retail trade, banking and financial activities as well as manufacturing activities (Bogliacino et al., 2013) and the general productivity increases (Dachs & Peters, 2014). In general terms, research has shown that job losses will affect weaker professional groups (Cirillo et al., 2018; Lakshmi & Bahli, 2020). Specifically, blue-collar jobs have the highest risk of being replaced by automated systems (Manyika et al., 2017).

Regarding the positive perceptions associated with innovation, recent studies have shown that economic growth is positively correlated with financial development and innovation (Maradana et al., 2019; Pradhan et al., 2018) as well as productivity and competitiveness (Carayannis & Grigoroudis, 2014; Kafetzopoulos et al., 2015). Innovation also strengthens sustainability, since it is one of the current ethical aspects related to technological and engineering development (Verheyen & Peterson, 2020) and although there are ethical risks (Méndez-Suárez et al., 2023) that may cause reputational concerns affecting financial performance (Febra et al., 2023), many MNCs are investing in developing sustainability-orientated innovation (Geradts & Bocke, 2019) with the aim of meeting market demands that are increasingly orientated towards sustainability criteria (Fornes et al., 2019) and investment associated with corporate social responsibility (Monfort et al., 2021).

Considering that the robot and AI industries are amongst the most innovative in the world and that individuals use a process of generalization to form attitudes about new situations, we consider it to be relevant to propose the following hypothesis.

H1. Attitudes towards innovation impact opinions towards AI.

To determine the best way to bring innovative digitally-intensive industry closer to potential users, it is also decisive to examine the set of effects of the potential users' socio-demographic characteristics. Previous studies have analysed the role of age, sex, cultural background, and other user-related characteristics that are fundamental to understanding AI acceptance (de Graaf & Ben Allouch, 2013), although not in conjunction with the attitude towards innovation as a precursor. Sex plays a fundamental role in the perception of robots (de Graaf & Ben Allouch, 2013; Ivanov & Webster, 2019), as women are more reluctant towards AI than men for a variety of reasons (e.g. Kuo et al., 2009; Schermerhorn et al., 2008; Scopelliti et al., 2005). Also, research widely argues that understanding the impact of sex plays a crucial role in the perception of these devices based on AI (de Graaf & Ben Allouch, 2013; Ivanov & Webster, 2019; Schillo & Ebrahimi, 2021). Most studies argue that males have a better perception and consider AI as more socially desirable than females (e.g. Kuo et al., 2009; Schermerhorn et al., 2008); in addition, robots are essentially perceived by females as male entities, a particularly relevant hypothesis for the gender-sensitive design of humanoid robots (Parlangeli et al., 2023).

Age significantly influences attitudes and willingness to use new technologies (e.g. Kuo et al., 2009; LaRose & Eastin, 2004). Research has shown that ageing societies have a more positive view toward robots although, on an individual level, older people have slightly more negative attitudes toward this type of technology (Gnambs & Appel, 2019) and they are more hostile to robots (Hudson et al., 2017). For instance, Scopelliti et al. (2005) showed that older people significantly mistrust new technologies since they are less familiar with them. The literature also argues that the decline in the use of technology in older people is due to anxiety and a sense of low self-efficacy (Czaja et al., 2006).

In addition, people with a higher level of education are more likely to accept new technologies (Czaja et al., 2006; Rice et al., 2019), and people of lower socio-economic status perceive robots and AI worse (Gnambs & Appel, 2019). All in all, we state the following hypothesis:

H2. Socio-demographics moderate the relationship between innovation and opinions about robots/-AI.

3. Data and methods

3.1. Data

This research is based on a secondary analysis of the innovation barometer survey (Innovarómetro, 2018), carried out through in-person interviews amongst Spanish citizens aged 18 and older; the survey sampling was representative of the national population. It covers a wide area of questions related to innovation and robotic applications and includes a set of attitude measures towards innovation. Although the database contained a sample of 6308 observations, after removing all the answers corresponding with ‘do not know’ or ‘did not answer’, the number valid of observations was reduced to 3005 (1368 female and 1637 male). The sample description of the variables used in this research is in Table 1.

To investigate the opinion towards robots and AI, we analysed the answer given to the following question: “In general, regarding robots and artificial intelligence, do you have a very positive, positive, (neutral, not shown), negative or very negative point of view?”. After reversing the scores, the final measure is a scale from very negative 1 to very positive 5.

To investigate the attitudinal variables towards innovation, we analysed the answer given to the following question: “Do you agree very much, quite a lot, little or not at all with each of the following statements? The innovation…” (the questions are reported in Table 2). After reversing the scores, the final measure is a scale from don’t agree 1 to very much agree 4. The translations from Spanish to English for all the questions and answers were done by the authors.

3.2. Methods

To verify the proposed hypotheses, NMDS mapping is adopted to capture the innovation-related variables moderated by demographics that most affect consumers’ positive or negative opinion of robots. Before proceeding to the analysis, we briefly explain the NMDS methodology and its previous applications.

Table 2
Questions related to the attitude towards innovation.

Variable name	Question
Essential for growth	It is essential for economic growth
Improves competitiveness	Improves companies’ competitiveness, makes them more profitable, etc.
Improves quality of life	Increases people’s quality of life
Improves access to products	Improves access to products and services for all citizens
Improves sustainability	Enables the development of clean energy sources and sustainable development
Job losses	It causes jobs to be eliminated because companies need fewer workers
Loss of traditions	It causes the loss of traditional customs and lifestyles
Worsens f2f communication	Worsens face-to-face communication
Unnecessary consumption	It causes unnecessary consumption
Difficulties to adapt	Makes it difficult for many people to adapt to innovations

Visual ordination and mapping of information is one of the most informative methods to transfer large amounts of information for humans, due to their physiological features of perception (Krak et al., 2020). In particular, ordination and mapping techniques, such as NMDS, allow researchers to explore similar structures amongst objects in a multivariate dataset and graph them in a two-dimensional space so that the distances correspond to dissimilarities between objects (Kindt & Coe, 2005; Kruskal, 1964; Mair, 2018; Paule-Vianez et al., 2020).

In the present research, the NMDS maps show two-dimensional graphs of groups of individuals, grouped on their opinion about robots and ordered by their age or socio-economic status moderated by sex, so that distances represent their opinion about robots. Once the groups of individuals and their opinions are plotted on the map, an additional dataset with measures of the attitude towards innovation is included in the model, resulting in significant vectors that point to the area where that variable is most influential. The length of the vector represents the strength of that variable and is proportional to the correlation between the variable and the ordination. Vectors with similar angles indicate a correlation or coincidence of the attitude towards innovation of the different groups; vectors with angles around 90 or 270° indicate no correlation amongst the opinion of the different groups; and angles around 180° mean a strong negative correlation.

The quality of the ordination map is measured with the goodness of fit or stress of the model, which represents the rank order disagreement between observed and fitted distances. Low levels of stress imply high levels of non-metric fit R^2 between the ordination distances and the original dissimilarities. To find the specific contribution of each point to the misfit, the stress-per-point (SPP) is measured; points with high SPP should be analysed and the decision made to include that point or not. To be sure of the mediating effect of sex on opinions about robots based on age and status, the permutational multivariate analysis of variances, or Anova (Anderson, 2001) is calculated.

Table 1
Description of the sample. Number of respondents and percentage of each group by age and status.

Age	Female	Male	Total	%	Status	Female	Male	Total	%
18–24	101	134	235	7.8	Worker	195	109	304	10.1
25–34	228	256	484	16.1	Skilled Worker	212	544	756	25.2
35–44	297	381	678	22.6	Lower-Middle	156	226	382	12.7
45–54	310	322	632	21.0	Middle	408	310	718	23.9
55–64	208	283	491	16.3	Upper-Middle	397	448	845	28.1
65 +	224	261	485	16.1		1368	1637	3005	100.0
	1368	1637	3005	100.0					

All NMDS analyses were carried out using R version 4.1.2 (R Core Team, 2021) using the package *vegan* (Oksanen et al., 2019) for the creation of the NMDS model and the package *ggplot2* (Wickham, 2009) for the graphs. The data and R code to replicate the NMDS maps can be downloaded at Méndez-Suárez et al. (2023).

4. Results

The resulting bidimensional NMDS maps are in Fig. 1(a) for age and Fig. 1(b) for socio-economic status. Groups close to each other in ordination have similar opinions about robots and similar attitudes towards innovation. Two groups far away from each other in ordination have different opinions about robots, and consequently different attitudes towards innovation.

Values of the axis are not shown as they are not interpretable. Arrows represent the significant attitudinal variables towards innovation (p-value < 5%) and point to the direction where the variable has a greater influence on the opinion towards robots and AI. Abbreviations: *F* = Female, *M* = Male; UMI = Upper Middle class, MI = Middle class, LMI = Lower Middle class, SW = Skilled Worker, *W* = Worker, VN = Very Negative, *N* = Negative, NE = Neutral, *P* = Positive, VP = Very Positive.

Results of both maps in Fig. 1 show two-dimensional stress below 5%, with values of 1.31 and 3.30% for age and socio-economic status respectively, giving an excellent representation with no prospect of misinterpretation (Clarke, 1993). The non-metric fit R^2, between the ordination distances and original dissimilarities, is very high at 99.98 and 99.89% for age and socio-economic status, respectively. Bubble size around each group indicates SPP, small values point to a better fit, although in this case the size is rescaled since all the values are very low, with a maximum of 1.54% and minimum of 0.13%. Arrows represent the significant (p-value < 5%) attitudinal variables towards innovation. Table 3 summarizes the impact of these attitudinal variables towards innovation exerted in the opinion about robots and AI on both groups.

4.1. NMDS results on age

Fig. 1(a) shows the visual representation of proximities of the different age groups, arranged by sex, based on the similarity of opinion towards robots and AI and including the impact of the attitude about innovation. All the males, except those aged over 65, are located in regions with positive and very positive opinions about robots. In this region, the vector with the greatest impact in the positive attitude is the idea that innovation improves competitiveness, followed by the idea that innovation is essential for growth; younger people aged 18–24 are more affected in their positive opinion about robots and AI by the ideas

Table 3
Impact of the attitudinal variables towards innovation on the opinion about robots of the different groups based on the relative size of the gradient vectors.

Variable name	Impact on Age	Impact on Socio-economic status
Essential for growth	Medium	High
Improves competitiveness	Medium	High
Improves quality of life	Medium	Medium
Improves access to products	No	No
Improves sustainability	Medium	High
Job losses	High	High
Loss of traditions	No	No
Worsens f2f communication	Low	High
Unnecessary consumption	Low	No
Difficulties to adapt	No	Medium

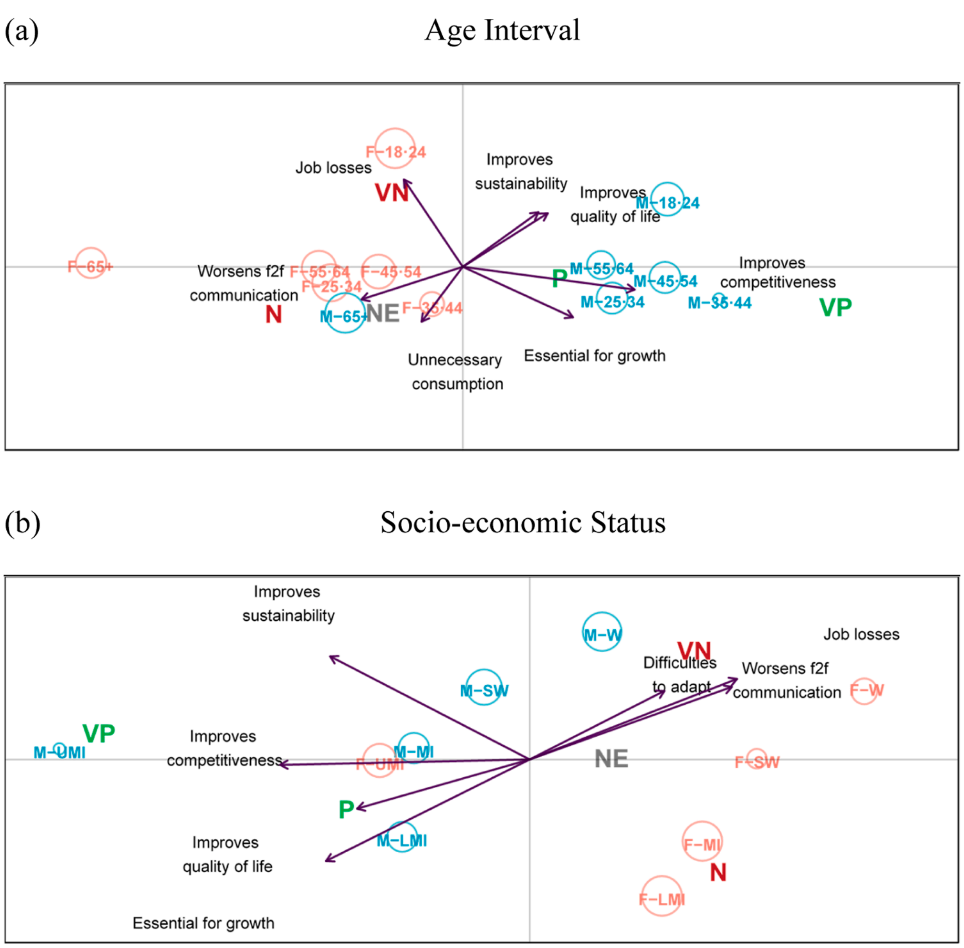

Fig. 1. NMDS analysis of the opinion about robots based on age (a) and socio-economic status (b) moderated by sex. Values of the axis are not shown as they are not interpretable. Arrows represent the significant attitudinal variables towards innovation (*p*-value < 5%) and point to the direction where the variable has a greater influence in the opinion towards robots. Abbreviations: *F* = Female, *M* = Male; UMI = Upper-Middle class, MI = Middle class, LMI = Lower-Middle class, SW = Skilled Worker, *W* = Worker, VN = Very Negative, *N* = Negative, NE = Neutral, *P* = Positive, VP = Very Positive.

that innovation improves sustainability and quality of life. Curiously, the vectors “Improves sustainability” and “Essential for growth” are almost orthogonal, meaning an absence of correlation, that is the ideas of growth and sustainability are not related.

On the other side of the plane are all the females; these regions concentrate the opinion about robots ranging from neutral to negative and very negative. Males older than 65 and all females, except the youngest and oldest, have an opinion from neutral to negative towards robots and AI, the drivers of these opinions are related to the opinion that innovation worsens face-to-face communication and stimulates unnecessary consumption. Females aged 18–24 have the worst opinion about robots, associating innovation with job losses. Females over 65, although having a negative opinion about robots and AI, are the most dissimilar to the rest of the groups.

Opinions on innovation related to the improvement of access to new products, the loss of tradition or the difficulties to adapt to innovation do not have an impact on the opinion towards robots and AI for these groups.

The permanova analysis (9999 permutations), ratifies the significant impact of age (p-value = 0.03%) and sex (p-value = 2.80%) in the opinion about robots. As expected, age with a large effect is the most relevant variable, explaining 82.90% of the ordination distance, versus sex, explaining only 13.48%.

4.2. NMDS results on socio-economic status

Fig. 1(b) shows the visual representation of proximities of the different socio-economic groups arranged by sex, based on the similarity of opinion towards robots and AI as well as including the impact of the attitude about innovation. All the males, except workers, are located in regions with positive opinions about robots and AI, with upper-middle class having a very positive opinion. In this area, the idea that innovation improves quality of life is highly correlated with the idea that innovation is essential for growth; both ideas exert their influence, pointing in the direction of a positive opinion towards robots.

On the upper right-corner, we may find male and female workers with very negative opinions about robots; this opinion is conditioned by the three vectors related to job losses, worse communication, which is closer to females, and difficulties to adapt to innovation. Those three vectors are in the opposite direction to those related to positive attitudes towards this technology, meaning a strong negative correlation. Skilled female workers are in the neutral region. Middle class and lower-middle class females are in the area of negative opinions, but none of the ideas analysed related to innovation affect their point of view; further research could try to find reasons for attitudes towards innovation that explain their opinion.

Opinions on innovation related to the improvement of access to new products, the loss of tradition or the generation of unnecessary consumption, do not have an impact on the opinion towards robots for these groups.

The permanova analysis (9999 permutations) ratifies the significant impact of socio-economic status (p-value = 0.01%) and sex (p-value = 2.22%) in the opinion about robots. As expected, social status has the strongest effect in the ordination distance, explaining 88.51% versus sex which, explains only 7.57%.

5. Discussion and conclusions

This study’s aim focuses on understanding consumers’ acceptance of AI-based products, unfolding innovation attitudes and social-demographic characteristics that influence attitudes towards AI acceptance. Cross-fertilizing these sub-lines of enquiry, we analyse 3005 observations from the Spanish Innovation Barometer survey using non-metrical multidimensional scaling (NMDS). In doing so, this study seeks to understand whether consumers’ attitude towards accepting AI is influenced by innovation attitudes and social-demographic characteristics, attempting to answer the following research questions: (1) Are attitudes towards innovation affecting opinions towards AI?, (2) Are socio-demographic dimensions affecting consumers’ acceptance of AI?

According to the results, the two stated hypotheses are confirmed. Results point out that (H1) attitudes towards innovation impact opinions towards robots and AI; in particular, results show that negative attitudes towards innovation are associated with negative opinions towards AI, while positive attitudes towards innovation are associated with positive opinions towards robots and AI. In addition, (H2) socio-demographics moderate the relationship between innovation and opinions about robots/-AI; in particular, age and sex moderate the relationship between innovation and opinion about AI and socio-economic status and sex moderate the relationship between innovation and AI.

Overall, our insights show that consumers showing a negative view towards innovation also maintain this attitude towards accepting AI. However, age and socio-economic status can moderate this significant relationship, making younger people with a good socio-economic status present a more positive opinion towards robots and AI. In addition, sex influences opinions, showing how being male affects the set of effects that age and socio-economic status have on opinions.

Results bring interesting contributions to literature. First, these primarily negative opinions towards AI strengthen previous theories based on the theory of reasoned action (TRA) (Ajzen & Fishbein, 1980) and shed new light on existing acceptance models of technology (de Graaf et al., 2019; Venkatesh et al., 2012). The data confirm previous studies that argue that perceptions towards innovation are a precursor to behavioural intentions and adoption of new technologies (Gnambs & Appel, 2019; Lee, 2012; Venkatesh et al., 2003; Wurthmann, 2014). Following studies that have examined how people use a process of generalization of attitudes when judging new situations (Pietri et al., 2013), the results allow us to sustain that the predisposition towards innovation can be generalized and predict opinions towards AI-based robots (Nomura et al., 2008; Song & Kim, 2020).

Second, the study shows socio-demographics influence the adoption of AI. In particular, results show that age and socio-economic status moderate the effect of opinions towards AI. Thus, these findings strengthen other studies that have examined how older people have more negative opinions toward this type of technology (Gnambs & Appel, 2019; Hudson et al., 2017) or mistrust new technology for not being familiar with it (Scopelliti et al., 2005). The results show that older people associate innovation with more negative attributes. In this way, the results provide new information about a research question that is still to be resolved: whether age matters in the use of AI (Belanche et al., 2020). Regarding socio-economic status, the results also show that people with higher socio-economic status have a better predisposition towards AI, which gives new information and strength to other studies that have observed that people with a higher level of education are more likely to accept new technologies (Czaja et al., 2006; Rice et al., 2019) and that less skilled workers observe robots more negatively (Gnambs & Appel, 2019).

The study also confirms the effect of sex in increasing willingness to AI. Thus, sex influence age and socio-economic status which determines the predisposition towards AI. The results shed light on previous literature which argues that sex has no clear impact on predisposition toward AI (Dinet & Vivian, 2014; Shibata et al., 2009) by strengthening those findings that support the relevance of sex in the acceptance of AI (e.g. Kuo et al., 2009; Schermerhorn et al., 2008; Scopelliti et al., 2005).

Overall, for scholars, this present study contributes to expanding the study of customers’ acceptance of AI from a different perspective that emphasizes: a) the relationship between attitude towards innovation and consumer technology acceptance, and b) the influence of socio-demographic factors on AI adoption. By introducing social-demographic imprints and innovation attitudes of consumers, this present study complements and expands the literature on drivers of AI (e.g., Mariani et al., 2023) going beyond traditional technology acceptance literature (TAM and UTAUT models) based on behavioural and social cognition (e.g. Meyer-Waarden & Cloarec, 2022), thus adding a new approach to the technology acceptance topic. Our conclusions could potentially impact company adoption of AI literature (e.g. Leung & Wen, 2020), as the study of the implementation of AI by firms in different industries (e.g. health, finance, etc.,) can be fruitfully cross-fertilized by using customers' socio-demographic variables to predict whether firm AI implementation could improve performance from a customer-based perspective.

The managerial implications of this study are evident. In the face of a growing industry with unparalleled growth potential, companies that develop or incorporate robots into their processes or services must be able to adequately reach potential users. For that reason, marketing and communication professionals need to understand that they should first send a positive message about innovation: a message linked to an innovation that is essential for growth improves competitiveness, improves the quality of life, improves access to products, does not affect the loss of traditions and improves sustainability. By improving these general opinions towards the concept of innovation, practitioners will be promoting a better predisposition towards robots. On the other hand, amongst the groups giving initial momentum to this market are young men with high socio-economic status. This data is essential to be able to propose word-of-mouth strategies or other types of promotion that can promote the acquisition of robotic devices. This article, therefore, offers a clear market segmentation and a penetration strategy based on prior improvement of attitudes towards innovation.

Amongst the limitations and areas of future research is that the question of AI acceptance is a general one, that encourages the notion that not everyone has a clear and holistic idea of the benefits of AI. It would be appropriate to raise this same model under specific criteria by type of AI application. In addition, the study does not include education as a moderating variable and it would be interesting to know if it influences the adoption of AI-based products. It could also be revealing to study more recent data following the introduction of AI applications such as ChatGPT and these new generative AI applications to see if attitudes have changed. Furthermore, the study focuses on Spain, but it would be interesting to also research the opinions of other European citizens.

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Appendix. OLS results on age and socio-economic status

To quantitatively verify the qualitative results of the NMDS map for age and the NMDS map for socio-economic status, we performed a multiple regression for each one where the dependant variable was the opinion towards robots and AI and the independent variables were all the attitudinal variables towards innovation, except those that were found to be non-significant in both maps: "Improves access to products" and "Loss of traditions". The results of each one of the multiple regressions are in Table 4.

In the regression for age, except for the variable "Improves sustainability", the variables are significant and have the same sign, thus verifying the results of the previous NMDS mapping. The impact of *age* is negative, meaning that as consumers get older their opinion towards robots and AI worsens.

In the case of the regression for *socio-economic status*, the results are also very similar to those in the NMDS map, with the same exception indicated above (variable "Improves sustainability") which is also non-significant. As for the impact of the *socio-economic status* variable, it has a positive effect, showing that as socio-economic status increases, the opinion on robots and AI also improves.

These results add further information to the analysis on the negative impact of age and the positive impact of socio-economic status on the opinion of robots and AI and also show robustness of results.

Table 4
Results of the regression, using only the variables significant in the NMDS map. The dependant variable in both cases is the opinion about robots.

	Age				Status			
	b	SE	t	p-Value	b	SE	t	p-Value
Intercept	3.254***	0.154	21.116	0.000	2.788***	0.151	18.464	< 2e-16
Essential for growth	0.131***	0.032	4.114	0.000	0.116***	0.032	3.646	0.000
Improves competitiveness	0.056*	0.027	2.022	0.043	0.047.	0.028	1.707	0.088
Improves quality of life	0.165***	0.028	5.881	0.000	0.169***	0.028	6.032	0.000
Improves sustainability	0.035	0.028	1.242	0.214	0.039	0.028	1.400	0.162
Job losses	−0.179***	0.022	−7.984	0.000	−0.159***	0.023	−7.061	0.000
Worsens f2f communication	−0.091***	0.022	−4.046	0.000	−0.083***	0.022	−3.722	0.000
Unnecessary consumption	−0.025	0.023	−1.096	0.273	−0.030	0.023	−1.285	0.199
Difficulties to adapt	−0.040	0.024	−1.640	0.101	−0.044.	0.024	−1.816	0.070
Sex Male	0.237***	0.034	7.059	0.000	0.252***	0.034	7.478	0.000
Age	−0.005***	0.001	−4.621	0.000	–	–	–	–
Socio-economic status	–	–	–	–	0.067***	0.013	5.319	0.000
Number of observations	3005				3005			
F-statistic & p-Value	49.33; 0.000				50.13; 0.000			
R^2	0.142				0.143			

Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1.

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