Robophobia in elderly care: An analysis of grey pressure, technology exposure and age.

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ABSTRACT,
The elderly population is growing, and this puts pressure onto health- and social care systems. While social robots present an opportunity to tackle this problem, the public perception towards using robots in care domains in Europe is low. Unfortunately, especially the older age groups are negative towards this idea. This research investigates the relationship between the public's perception on using robots in elderly care and age with a specific focus on the influence of demographic factors within a country as well as the general role of technological exposure. Also, the observed differences between European countries are investigated. Through a quantitative data analysis and literature review, the causes and potential solutions to this problem are discussed. For the data analysis, primary sources are the Eurobarometer survey conducted by the European commission as well as general demographic data from Eurostat and Statista. It appears that both older people and those with limited exposure to technology tend to have an increased fear for robots in elderly care. Proactively increasing exposure and investing in innovation reduces these current fears while new generations might experience different perceptions. This paper presents and discusses these findings in detail.

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Robotics, robophobia, technology, elderly care, demographic, aging, grey pressure

1. INTRODUCTION

1.1 Background

On a global scale, the elderly population is growing more rapidly than younger age groups, with the global population of those older than 60 years expected to reach two billion by 2050 (WHO, 2022). Population ageing is the result of two factors: falling fertility rates, and a higher life expectancy. With the former generally having a larger impact on population age structure. (Grundy et al., 2017) This growing ageing population in combination with shortages of healthcare professionals place enormous pressures onto the health and social care systems of many countries, especially in terms of elderly care.

The rise of artificial intelligence (AI) and robotics poses a solution to this challenge. This opportunity has been first considered and explored decades ago. The MOVAID project in 1994 was said to be one of the first robots implemented with the purpose of assisting the elderly and disabled through in-house activities such as removing bedsheets or microwaving food (Bardaro et al., 2021).

With the deployment of robots in the field of elderly care, we often refer to social robots. These social robots are aimed to have a close resemblance to human-to-human interaction in terms of behavior but can also potentially inhibit a humanoid form. AI-powered systems could help the elderly to live independently for longer by managing medication, monitoring health, and detecting concerning behavioral patterns (Padhan et al., 2023). Robots, also in combination with AI, could take care of physical daily chores such as cleaning and providing nutrition. Even tasks such as dressing which is seemingly more complex are already being developed and tested. An example is the two-armed dressing robot, demonstrated by Dr. Jihong Zhu at the University of York's Institute for Safe Autonomy (University of York, 2024). Besides services, robots and artificial intelligence can also perform emotional tasks. Emotional robots, such as the robot seal Paro, fulfill the specific psychological needs of interaction, communication, companionship, and attachment (Kolling et al., 2016).

It seems like machines could play an important role in taking care of a holistic set of caring tasks and the future outlook is promising. However, just like MOVIAD, the many robotics projects that followed and marginally built upon their precedent technologies often remained prototypes that did not find long term applications outside of lab environments. So far, there have not been any reported cases of social care robots entirely replacing the jobs that caretakers are thus far doing, providing a holistic set of tasks to care for the elderly at home or in nursing homes, both physically and emotionally.

Yet, given the urgency of the problem, unmet market demands, and current technological advances, it is a matter of time until robots are ready to be deployed in nursing homes for both emotional and physical purposes. However, another societal concern could create an obstacle in widespread deployment and adoption. Statistically, people in Europe generally have a negative attitude towards the idea of deploying AI and robotics in the social care system. According to a Eurobarometer survey conducted in 2017, about 30% of respondents in Europe feel totally uncomfortable about receiving services and companionship from a robot when elderly or infirm. This poses a contrast with the general attitude to robots in jobs that do not necessarily involve human interaction such as space exploration, manufacturing, and security which is seemingly more positive. As long as it remains unclear what exactly causes this fear, a widespread deployment and adoption of social robots will be challenging, even when issues regarding safety and effectiveness are resolved.

While technology, including future robotics, offer potential of improving quality of life, older adults do not adopt technology nearly as much as younger people do (Berkowsky et al., 2017). According to Berkowsky (2020), "Older adults are much more likely to consider adopting a technology if they perceive that it is of value to them and will positively impact their lives".

Another potential explanation of this attitude is the degree of which people are familiar with technology. The term "technology exposure" was used in earlier research by Pluart in 1996 to refer to the degree of experience one has with using technology for both work and leisure purposes. This can be extended to including types of exposure that do not include interaction although this is often the case. (Pluart, 1996)

Presumably, an increase in age itself does not automatically lead to fear of robots but rather it is the lack of exposure to technology which explains this behavior. This is often prevalent with older age groups.

Another consideration for this research is the influence of demographic pressure in countries which arises from demographic aging. This refers to the ratio of those aged 65+ to the working population aged between 20 and 65 years old. A larger grey demographic pressure would suggest a greater familiarity with the issue of aging demographic and the opportunities that robotics provide. Perhaps there is different behavior to be noticed in terms of acceptance of innovative approaches like the usage of robots. Although there are significant differences between the demographic population pressure in the EU countries, a general trend of ageing population takes place everywhere.

1.2 Research objective

In this paper there will be a specific focus on understanding the attitude to robots where it concerns applications and deployment in elderly care. The research is based on survey data from a highly diverse and large sample of European respondents. The results are evaluated based on the 27 EU countries, yet it is also likely that general insights on behavior can be applied on a global level. An analysis on international level should form a broad basis and highlight important differences and predictive factors.

The main objective of this research is to ultimately evaluate the effect that exposure to, or experience with technology has on people's perspective on using robots in elderly care.

If this appears significant, also taking into consideration other factors, conclusions and recommendations can be made about the urgency of dealing with this problem in society both now and with the outlook on future generations.

Thus, the research question is as follows:

What is the effect of technological exposure in the relationship between age and attitudes toward robots in elderly care among Europeans?

2. THEORY

Prior articles and research papers have highlighted important insights on the topic of robophobia in social care settings. The most important ideas and results will be talked about below as part of my research and to shape the direction via potential knowledge gaps.

3.1 Age on attitude

One of the main references for this paper will be the work done by Hudson et al in 2016 in the paper "People's attitudes to robots in elderly care". This research explores the age-attitude relationship in combination with other demographic characteristics such as education, gender, living situation, employment and location. It suggests that indeed older people are less comfortable with robots and the most hostile are women; people living in small towns, and those with a lower education.

Another important conclusion is made when comparing the elderly's attitudes to robots when it concerns different jobs. Seemingly, they are less hostile towards the idea of deploying robots in education than when it concerns elderly care, which they are, of course, directly impacted by (Hudson, 2016).

3.2 Industrial to social

Prior research by Taipale et. Al (2015) highlights the shift from robots in industrial production to social reproduction. Using a similar Eurobarometer dataset, this paper revealed that there is significantly less support for robots in the domains of social reproduction such as education or health- and elderly care. This is relevant for understanding that there is a difference in the acceptance of such technology based on the domain. Industrial robots are commonly used in public workspaces while the domestic ones enter a private (less controlled) environment.

3.3 Robot acceptance

A paper by Venkatesh et al. discusses different models for technology acceptance which led to the construction of the first Unified Theory of Acceptance and Use of Technology (UTAUT) which is considerably more inclusive and successful over precedent models. (Venkatesh et al., 2003) The UTAUT model (1) considers performance expectancy, effort expectancy, social influence, and facilitating conditions as well as the moderating influence of gender, age, experience, and volutariness, to explain user intention and behaviour. An extended model of the original UTAUT includes the additional variable of technological anxiety to influence the use attitude of a new technology (Nysveen et al., 2016). This was designed for research on consumer behaviour on new RFID[1] technology related to the intrusiveness of the system which can be closely linked to the attitude of people towards unknown robotic technology in the context of elderly care.

A mixed-method study by Wu et al. demonstrates that the factors from the UTAUT model can be applied for "robot acceptance" research and provides an extensive analysis of this acceptance with elderly people (Wu et al., 2014). The paper mentions common barriers to robot acceptance and fear (or anxiety) is one of them. This study will be fundamental for the analysis and discussion sections.

3.4 Generational differences

When we compare different age groups regarding their technology acceptance, there are inherent differences. A paper by Hanson in 2011, "Technology skill and age: what will be the same 20 years from now?" mentions the experience factor. Whether or not one is growing up with computers and other devices plays a crucial role in accepting and using new technologies. Although this research is somewhat old and relates to the general concept of (digital) technologies instead of robots, it is useful for later discussion.

The aforementioned study by Wu et al. also touches upon this topic. Many elderly participants in this research mentioned that their generation does not get used easily to technology, and they believed new "cohorts" of old people would be less reluctant towards robots.

Research by Pruyt et al. focuses on the consequences of this increasing demographic pressure in the areas of health care, labor market, housing and social security. Falling fertility rates with higher life expectancies cause an increase in shift from those participating in the labor market, to those in retirement and in need of social assistance. Consequently, the expenditures for health care rise with less money available to cover for it (Pruyt, 2011).

3. METHODS

This research employs a secondary quantitative data analysis. The main source of data and analysis is the Eurobarometer survey on the "Attitudes towards the impact of digitization and automation on daily life", conducted in March of 2017 (N = 27901) (European Commission, 2017). The survey questions are close-ended and discuss topics like digitalization, automation and lifestyle. Multiple statistical analyses are performed using data analysis software RStudio. The main variables used will be introduced below and further dissected in appendix table 1 for reference.

The education score of a country is calculated by taking the number of students enrolled in tertiary education[2] divided by the total population. Note that the number of students would usually be less in countries with higher grey pressure but as shown in the analyses above, this does not influence perceptions, so this regression remains valid.

[1] RFID = Radio frequency identification

[2] Tertiary education includes all types of post-secondary education at universities or colleges.

The GERD[3] variable reflects the total amount spent on research and development in a country. This is taken as a percentage of the total GDP (Gross Domestic Product). This is a typical measure for the degree of innovation and technological advancement. Presumably, a higher GERD correlates with a higher perception.

How much a country spends on the older population is covered within the "Old age" variable (The name is copied from the original data). Precisely, this refers to the expenditure on elderly benefits as a percentage of GDP (Gross Domestic Product) by the government.

After first confirming the age effect with this data for Europe, it will be analyzed for the different EU countries and the degree of grey and green demographic pressure in those countries. Green pressure is the ratio between the number of people aged 0-20 and those aged 20-65 and grey pressure is the ratio between the number of people aged 65+ and those aged 20-65. This would help draw conclusions and write recommendations on the level of green/grey pressure in a country. Data from Eurostat on population structure in 2017 will form the basis for this part.

The second part of the research consists of theories and literature review to evaluate the broader context of the research such as demographic factors and understanding (future) scenarios that relate to the analytical results. This part also involves finding out more about the adaptability of technology as one grows older in order to support possible conclusions.

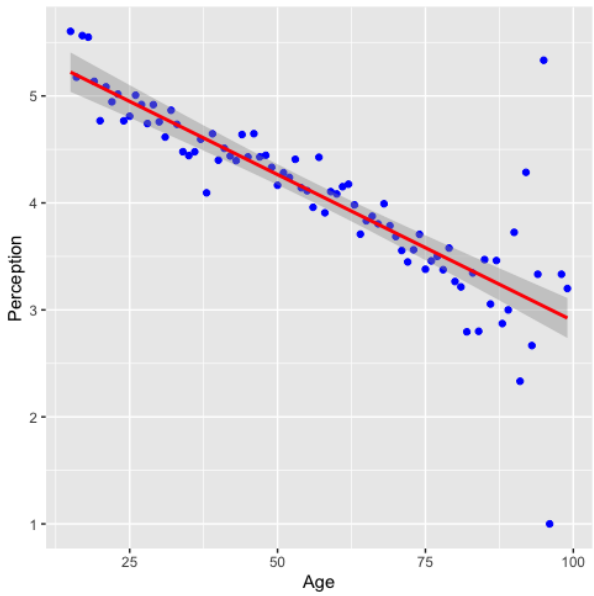
This method is used because of the rich and reliable nature of the already available Eurobarometer dataset which provides room for elaboration based on new insights and ideas during the research. Additionally, a quantitative approach allows for more objective and extensive results. Another benefit is that there is sufficient prior literature that utilizes the same dataset for a similar topic which enhances and supplements this research.

4. RESULTS

At the start of this research is finding a deep understanding of the age-attitude graph as also proposed by the research from Hudson et al. The graph in figure 1 is the result of a regression analysis of age against the averaged perception towards robots in elderly care. For a broader connotation, here the term perception is used to refer to how people think about robots. This scale goes from 1 (totally uncomfortable) to 10 (totally comfortable)

[3] GERD = Gross domestic Expenditure on Research and Development

Figure 1: Scatterplot of age on perception of receiving services by robots when elderly or infirm. Source: Eurobarometer 87.1

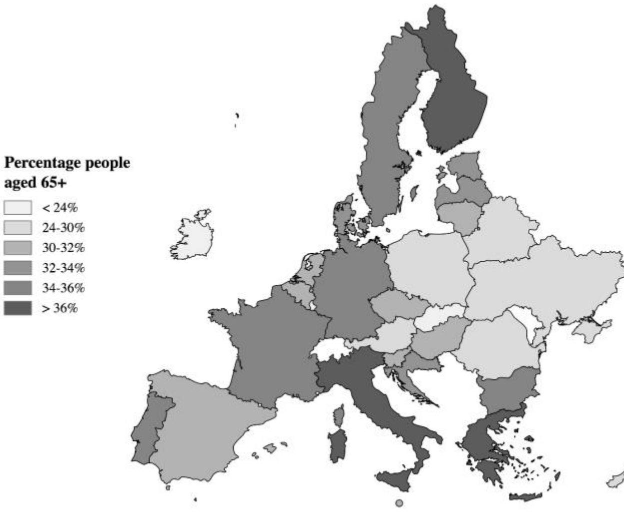


There are two important insights to notice and remember moving forward. First, like expected, there is a clear and significant negative correlation between age and perception; older people are less comfortable with the idea of receiving care of intelligent machines. Secondly, the general perception does not rise much above 5 and is seemingly low for the majority of age groups.

Zooming in on the individual EU countries not only helps understand the severity of the problem and effect of age for all countries but also characteristics of these countries can help understand the relationship better. Considering the topic of ageing population, a special interest is shown in the grey demographic pressure. This variable concerns the amount of people aged 65 or older as a percentage of the general working population aged 20 to 65.

Using MapChart.net, a map was created for the calculated grey pressure values for all EU countries which be seen in the figure below. Ireland and Slovakia have the lowest grey demographic pressure, while Italy, Greece, and Finland have the highest share of elderly people as of 2017. Despite a couple exceptions, the map reflects a tendency for more Eastern located countries to have a generally lower percentage of people aged above 65 than the Western countries.

Figure 2: Grey demographic pressure in 27 EU countries in 2017. Source: Eurostat



It is expected that a higher share of elderly people in a country's population causes a higher level of comfort among older residents, thus lifting the right end of the age-perception slope, making it less steep. A reason for this could be that the debate about robots in elderly care in these countries is more relevant and more is done to reduce feelings of anxiety for future scenario's that involve assistive machines. An important consideration is the potential overrepresentation of older people in a random sample of a country with a higher grey pressure. Nevertheless, the age distributions (Appendix image 2) seem to approach normality and the exceptions do not match those countries with a higher grey pressure so this can be ruled out.

For each EU country, using the Eurobarometer dataset the absolute perception over all ages is combined and the slope of the association between age and perception which is used to test the potential modifier effect of grey pressure. The grey demographic pressure variable as introduced above is calculated accordingly based on age composition from Eurostat. These three values are given for each country in appendix table 6.

In table 1, the relationship between grey pressure and average perception is tested using a regression analysis. Average perception is the dependent variable and grey pressure is the independent variable. As it is an exploratory analysis, no control variables are included

Table 2 shows an analysis of the modifier effect of the variable "grey pressure" on the aforementioned age-perception relationship in the individual countries. This relationship is presented as the variable "correlation".

Table 1: Regression of grey pressure on average perception ($\alpha = 0.05$)

Variable	**Estimate**
(Intercept)	-0.650 (3.629)
Grey pressure	4.416*** (1.139)
R squared	0.001
Adjusted R squared	-0.039
Residual std. error	0.744 (df = 25)
F statistic	0.032 (df = 1; 25)

Table 2: Regression of modifier grey pressure on age-perception correlation ($\alpha = 0.05$)

Variable	**Estimate**
(Intercept)	-0.00638 (0.0942)
Age-perception	-0.525* (0.300)
R squared	0.109
Adjusted R squared	0.073
Residual std. error	0.064 (df = 25)
F statistic	3.062* (df = 1; 25)

The results of table 1 show an intercept of -0650 (SE = 3.629) and a significantly positive coefficient for grey pressure ($P < 0.001$) which suggests that higher grey pressure correlates with higher perception. However, there is no sufficient variance explained ($R^2 = 0.001$, Adjusted $R^2 = -0.039$) and the model itself is not significant ($P > 0.05$). This conveys that although grey pressure has a statistically significant effect, by itself it does not explain differences in perception sufficiently.

In table 2, there is an intercept of -0.0638 (SE = 0.0942) and the coefficient for the correlation variable can only be seen as significant at the 10% level ($P < 0.10$). 10.9% of the variance in perception is explained in the model ($R^2 = 0.109$, Adjusted $R^2 = 0.073$). And the model appears to be a significant fit to the data ($F = 3.062$, df = 1, 25, $p < 0.10$). The results indicate that grey pressure may have an impact on the age-perception slope but there is no strong enough evidence at $\alpha = 0.05$.

Neither of the models return values that allow for a concise and scientifically relevant insight. Apparently, the age composition within a country does not indicate the overall attitude a country has on the deployment of robots in elderly and health care.

Additionally, the share of old adults (65+) in a country's population does not sufficiently explain the steepness of the age-perception value or the likelihood for older people to have a more negative attitude towards robots.

Still, there are clear differences to be seen between the countries' perception on the use of robots in elderly care. Appendix table 2 tells us that the scores range from a mere 2.51 in Cyprus to a (still somewhat moderate) 5.77 in Poland on the comfort scale. This difference is noteworthy considering they are averages in a large sample. This raises the question why these countries deviate so much from the average and what can be learned from that. This implies that there could be other demographic or economic factors that explain these differences.

The general level of education in a country could potentially explain this, as prior research also highlighted that lower levels of education relate to lower perceptions (Hudson et al., 2016).

The values for these variables are derived and calculated using data from Eurostat and tested in a multiple regression model with the country's average perception as the dependent variable. The results are displayed in table 3 and discussed below.

The expenditure on R&D as a percentage of the GDP (GERD) has a statistically significant positive relationship with perception (P = 0.042). In other words, citizens in countries with a higher degree of innovation are generally less fearful towards the usage of robots in elderly care. Another significant correlation can be found with the "Old age" (name taken from the original data) variable (P = 0.0375) at the same 5% significance level. It seems apparent this also contributes to a positive perception in the sense that the government takes good care of the elderly and thus the systems to deploy robots would be trusted as well.

Surprisingly, on a country level, education does not seem to be significantly related to the average perception (P = 0.0835). However, the negative relationship is indeed present and would be accepted at the 10% significance level. It could be that the result here is less obvious because of differences in sample and confounding effects of the other variables.

In the overall model, the R-squared value of 0.264 indicates that approximately 26.4% of the variance in perception is explained by these predictors, with an adjusted R-squared value of 0.130. The overall model is statistically significant (F(4, 22) = 1.974, P = 0.1338), suggesting that the included variables collectively provide a meaningful explanation for the variation in perceptions of robot use in elderly care across countries.

Table 3: Multiple regression, dependent variable perception ($\alpha = 0.05$)

Variable	**Estimate**	**Std. error**	**T-value**	**P-value**
(Intercept)	6.219	0.968	6.426	1.82e-6***
GERD	0.605	0.280	2.159	0.0420*
Education	-0.040	0.0222	-1.813	0.0835
Old age	-0.147	0.0663	-2.214	0.0375*
R squared	0.264			
Adjusted R squared	0.130			
Residual std. error	0.708			
F statistic	1.974 on 4 and 22 Df			

On the individual level, the perception one has towards the use of robots in elderly care is expected to depend on several factors, closely related to technology acceptance models like the UTAUT. However, the degree to which a person is comfortable to receive services from robots as an elderly person is only partly caused by the effort expectancy and performance expectancy introduced in such models. The extended UTAUT model as introduced by Nysveen and Pedersen (Nysveen et al., 2016) is based on a similarly technology and includes the relevance of technological anxiety or fear.

The general low perception score, retrieved at the start of the research is not indicative of the general attitude when it comes to robots and AI as it heavily depends on the industry in which they are deployed. As mentioned before, using robots in the domain of health and elderly care is a much more intrusive and intimate idea with less support than the deployment of robots in industrial jobs like manufacturing.

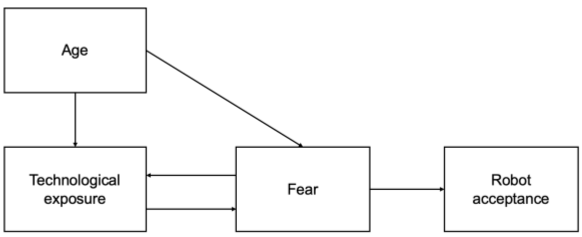
Therefore, while keeping in mind the relevance of other UTAUT dimensions, it is assumed that fear takes a prominent role in the model and in explaining acceptance or the lack thereof. Note that, considering the referred extended UTAUT model by Nysveen et al., the variable fear is introduced which is simply the reverse of the perception variable. Another argument for using fear is the emphasis on robot acceptance rather than technology acceptance. The idea of social robots comes with new emotional barriers such as distress and feelings of invasiveness and privacy risks.

The following analysis puts focus on the effect of technology exposure on the fear-related behaviors of people in the EU considering that older adults and digital immigrants living now do not get as much experience using modern technologies as their younger, digital native counterparts that grow up with it. This is confirmed with the data and can be seen in appendix table

It is expected that technology exposure has a positive effect on the perception of robots in elderly care. A higher experience with using modern technology would reduce the fear of being cared for by a machine in a later stage in life. Presumably, this would be the real predicter of fearful perceptions, correlated to the confounder variable of age. It was confirmed at the start of this research that age appears to influence fear. Nevertheless, age certainly has an inverse relationship with technological exposure too. Lastly, those that are fearful of robots are less likely to expose themselves to interacting with them.

This creates the following research model in Figure 3.

Figure 3: Proposed age-exposure research model



Technology exposure, in this context is defined as the degree to which people are exposed to technology in their life through hands-on experience. This is difficult to measure directly but can be estimated based on people's technological and digital competence. To make a prediction of the level of technological exposure among survey respondents in the most accurate way, a new variable is created based on the values of three unique questions. Individually the responses may not accurately predict whether someone can be considered to have a high "tech exposure", but respondents that score high on all these questions combined are highly unlikely to inhibit a lack of technological familiarity in the context of the general sample.

Survey questions for composite variable technological exposure:

Q D43b: Do you own a personal mobile telephone?

Q D62.1: How often do you use the internet at home?

Q D4.1: To what extent are you sufficiently skilled in the use of digital technologies in your daily life?

The internal consistency between these questions was measured with Cronbach's alpha of $\alpha = 0.692$ with a standard error of 0.03. This indicates that relationship between these variables is acceptable but not great.

The result is the variable for technology exposure ranging from 0 to 5 with a distribution skewed to the left. Regressing exposure on fear provides a quick visualization of a seemingly negative relationship as can be seen in the scatterplot of figure 4. To fully understand the relationships in the acceptance model, three regression models are tested, the results of which are outlined in table 4. Model 1 tests the effect of age on fear, model 2 tests the effect of exposure on fear, and model 3 tests the combined effects of exposure and age. In model 3 it becomes clear how each variable affects fear independently while controlling for the other. In other words, what is the effect of exposure on fear when age is present and vice versa.

Figure 4: effect of exposure on fear scatterplot

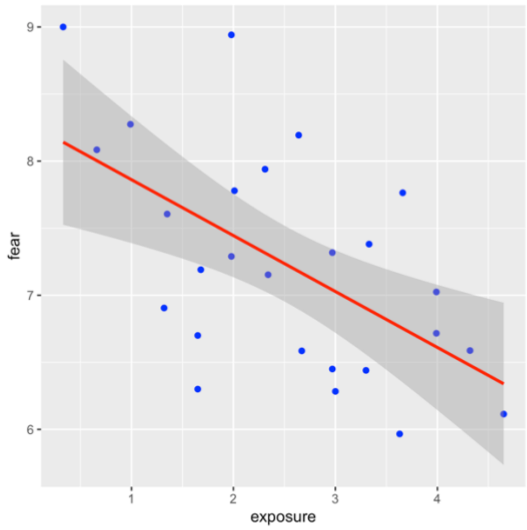


Table 4 – Regression analysis for dependent variable fear ($\alpha = 0.05$)

Variable	Model (1)	Model (2)	Model (3)
(intercept)	5.353 *** (0.0542)	8.240 *** (0.0794)	6.479 (0.108)
Age	0.0278 *** (0.000996)		0.0244 *** (0.00103)
Tech. exposure		-0.392 *** (0.0207)	-0.256 *** (0.0213)
R2	0.0282	0.0132	0.0726
Adjusted R2	0.0281	0.0131	0.0725
Residual Std. Error	2.976	2.998	2.968
F-statistic	778.6 (1 on 26884 Df)	358.3 (1 on 26884 Df)	463.8 (2 on 26883 Df)

The regression analysis of model 1 and 2 in Table 4 confirms a statistically significant positive correlation between age and fear and the negative correlation between exposure and fear with a significant negative coefficient at the 5% level as predicted. Higher technological exposure is indeed correlated with lower levels of fear.

As can be seen in the visualization at the start of this paper, the (negative) perception, or fear, significantly increases as people age. For every year increase in age, the scaled perception decreases with 0.03. Combined, this may indicate that exposure is the real driver of the reduced amount of fear when it comes to robots in elderly care.

Model 3 tests for the confounding effect of age. The results show that both exposure to technology and a person's age influence fear ($P < 0.05$). A comparison of the R-squared values tells us that model 3 has the highest value ($R2 = 0.0762$), and therefore combining age and exposure explains differences in fear better than the individual factors.

Still, all R-squared values are relatively low, indicating that there are other factors unaccounted for that would explain the rest of the variability in fear. This makes sense in the context of a broader technology acceptance model where other dimensions are present.

5. DISCUSSION

In contrast to domains where the anticipated use of robots is positively received, we are generally more hesitant when it concerns machines playing a role in our private lives and the idea of relying on their services when elderly. Especially the older age groups, who are at the center of the situation, seem to have an even more negative perception towards robots.

It seems like there is a lot of work to be done when it comes to reducing the people's fear and raising the level of acceptance. But exactly how severe is this problem and what strategies should be implemented to result in a higher acceptance over the course of the next decades?

Perceptions differ among EU countries, but this cannot be explained by the grey demographic pressure that is present. Expenditure on R&D and elderly care, however, do predict a lower fear of robots which is an important insight that ties in with the results of the effect of technological exposure. When a country is more technologically advanced, citizens would have a higher exposure to technology and therefore experience a higher acceptance. Government expenditure on elderly services also have an impact but this is already expected to increase as a result of aging population.

While all countries will have to face this issue, the urgency and the plan of approach will differ. For example, Italy and Greece both have a significant grey pressure and therefore have a higher urgency of tackling this problem. Nevertheless, the perception in Greece is relatively low so they might not resort to widely using social robots in the first place.

Table 4 demonstrated that both exposure and age play a significant role, and exposure alone cannot substitute the age variable. Factors inherent to aging such as health concerns or simply the distance from the situation (Elderly care by robots is a distant scenario for younger people) likely contribute to fear regardless of their exposure to technology.

An important consideration for the age-exposure relationship is that in the current time, older people typically are less exposed to technology because of the perceived challenges that come with technology while, except for the very young, younger age groups tend to have more hands-on experience with technology. This will likely turn around in the next decades where the new generations of elderly people are those that benefit from both being born in a digital era and having spent a whole lifetime adapting and gaining experiences with various innovations.

There is already a trend happening for the increase of older tech users. While populations are collectively adopting technology more often, people aged 65 or older show the highest growth. The percentage of this age group owning a smartphone has gone from 13% in 2012 to 61% in 2021 among people aged 65 and older. (Blazina, 2024)

Industrial robots being around for longer and receiving less resistance than social robots could also support the argument that exposure reduces fear, and that this problem is partly solved given sufficient time. We are simply not used to the idea of social robots yet. Insights by Wu et al. adds to this by implying that new generations could indeed grow old and remain less fearful and more accepting of being cared for by robots (Wu et al., 2014).

However, as the research by Hanson points out, ageing also brings a change in perceptual, physical, and cognitive abilities, making it harder to use new technologies. (Hanson 2012). This would not necessarily increase fear but impact dimensions in the UTAUT model, such as effort expectancy, and still cause a lower acceptance.

This remains a highly complex topic simply because no one knows how technology will advance and how well both young and old people will adapt. Being skilled with technology does not imply the willingness to include it in our private lives per se.

For the older adults that fear technology right now and those that have an inherent resistance to using technology Sherrill et al. (2022) recommends the following exposure approach. "(1) seek modeling and guidance from an experienced user, (2) engage slowly and deliberately, (3) learn one task at a time, (4) allow enough time to learn new information such observing that discomfort reduces over time and that one is more capable than originally thought, and (5) repeat the exposure until new adaptive information is learned." (p. 550)

6. CONCLUSION AND RECOMMENDATIONS

There is indeed a notable difference between the elderly and younger age groups when it regards perceptions about robot deployment in elderly care settings. While general perceptions are low when it comes to robots in social or domestic domains, older people are generally more fearful. Between the EU countries, differences in perceptions towards robots in elderly care can be partly explained by how much the government spends on R&D investments and elderly care.

Fear, age and exposure are closely related, and all seem to have an impact on technology or robot acceptance. It appears that both older people and people with limited exposure to technology tend to have an increased fear for robots in elderly care. Significant differences between EU countries would call for different approaches to increase robot acceptance. Generally, proactively increasing exposure and investing in innovation reduces these current fears while new generations might show higher perceptions. An increase in older tech users, exposure over time, and a shift in generation to digital natives, are all arguments that suggest that age will be less irrelevant.

Yet, low variances in some of the models presented indicate that there are additional variables to be considered for a holistic understanding of the topic.

Firstly, this calls for thorough examination of age-related factors and the effect on fear on an individual level. To be able to better understand the psychological drivers of fear towards robots among elderly, more tailored research should be conducted. This would include interviewing elderly people about their experience using robots, emotional states, and what potential risks they perceive.

Moreover, the forms and functions robots in elderly care can take is highly varied. One might be totally fine with a robot that cleans and talks to you but will show resistance to a machine that can track and predict personal health data. Understanding these personal nuances through additional questions specifying the type of robot is crucial for understanding the real fears better.

In terms of location, similar research can be focused on a specific EU country to understand the issue deeper in that country and how this compares to the rest of Europe to provide a framework for other countries that deal with similar problems.

Furthermore, it could be extended to analyze the situation in the rest of the world. Although the EU has cultural differences itself, continents such as Asia would have radically different cultural dynamics and properties that would make a comparison insightful. Particularly interesting would be the case of Japan where almost a third of inhabitants is aged 65 or older (WEF, 2023). When a similar fear effect is present, this could cause even greater issues.

Lastly, there were a couple limitations the means of analysis and secondary data used. Despite being from a reliable source, the research survey may not include the specific questions and answers that are tailored to this specific topic and its context. For this reason, particular questions need to be taken with a degree of uncertainty due to necessary assumptions about the respondents.

Lastly, no matter the extensiveness of the questions asked in the survey dataset, there remains a degree of interpretation and subjectiveness, of which the nuances would be better determined through qualitative interviews. An example would be the visual perception of robotics that would differ greatly for everyone. This can, of course, also cause inaccuracies in determining levels of fear in the overall sense of elderly care robotics.

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8. APPENDIX

Table 5: Variable operationalization table

(All data is taken from 2017 to match the Eurobarometer dataset)

Variable	Definition	Data Source	Measurement
Age	Age in years	Eurobarometer Survey: Q D11 Eurostat	Continuous variable between 15 to 99
Perception	How comfortable one is with receiving services from a robot when elderly.	Eurobarometer Survey: Q D13: How comfortable would you feel with having a robot provide you services when elderly or infirm?	Scale of 1 to 10
Fear	The inverse of the perception variable	N/A	Scale of 1 to 10
Grey pressure	the number of people aged 65 or older as a percentage of the general working population aged 20 to 65.	Eurostat	Ratio as percentage
Technology exposure	The degree to which people are exposed to technology in their life through hands-on experience. Value derived from three survey questions.	Eurobarometer Survey: Q D43b: Do you own a personal mobile telephone? Q D62.1: How often do you use the internet at home? Q D4.1: To what extent are you sufficiently skilled in the use of digital technologies in your daily life? Scores standardized and equally weighted.	Scale of 0 to 5
GERD	Gross domestic Expenditure on Research and Development	Statista, Eurostat	Percentage of GDP
Education	The number of students enrolled in tertiary education divided by the total population in a country	Eurostat	Percentage of total population
Old age	Percentage of GDP spent on elderly benefits and services.	Eurostat	Percentage of GDP

Table 6: Age-perception and grey pressure values in EU countries

Country	Average perception	Age-perception corr.	Grey pressure
Belgium	4.61839	-0.156	0.31186
Bulgaria	4.42071	-0.273	0.34210
Czechia	5.44731	-0.16	0.30718
Denmark	4.85324	-0.0193	0.32702
Germany	4.52313	-0.1435	0.35157
Estonia	4.23418	-0.26	0.32387
Ireland	4.028	-0.146	0.22881
Greece	2.75450	-0.145	0.36440
Spain	3.56294	-0.244	0.31045
France	4.47183	-0.116	0.34280
Croatia	4.19863	-0.171	0.32396
Italy	3.99485	-0.266	0.37605
Cyprus	2.51020	-0.162	0.24919
Latvia	5.03654	-0.205	0.33056
Lithuania	4.60714	-0.236	0.31900
Luxembourg	4.02579	-0.0116	0.22222
Hungary	3.75245	-0.14	0.30048
Malta	4.23565	-0.166	0.30322
Netherlands	4.554	-0.146	0.31302
Austria	4.30590	-0.217	0.29886
Poland	5.76785	-0.0893	0.26066
Portugal	3.16715	-0.264	0.35462
Romania	5.16966	-0.173	0.29132
Slovenia	3.01771	-0.18	0.30681
Slovakia	4.08544	-0.208	0.23291
Finland	4.00605	-0.121	0.36411
Sweden	4.41801	-0.166	0.34554

Table 7: Regression of age on exposure (α = 0.05)

Variable	Estimate
(Intercept)	4.4012*** (0.0115)
Age	-0.0131*** (0.0003)
R squared	0.07256
Adjusted R squared	0.07253
Residual std. error	0.851 (df = 26844)
F statistic	2103 (df = 1; 26844)

Image 1: Age distribution per country in Eurobarometer dataset

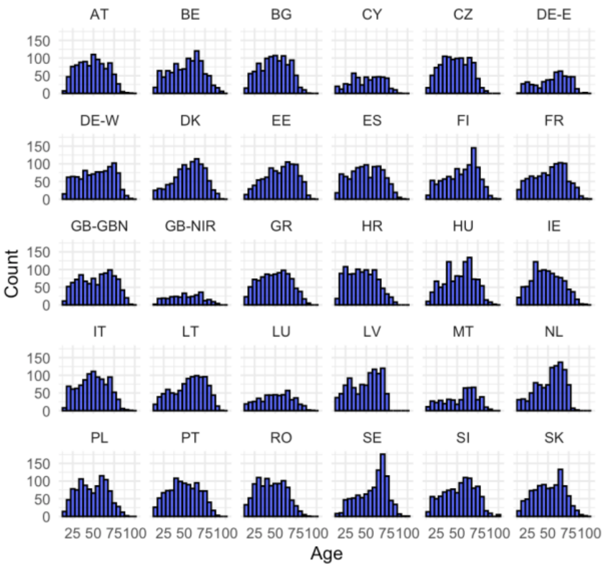

Image 2: Original UTAUT model (left) and extended UTAUT model (right)